Author:
Mottershaw, Abigail

Title:
Toward an Understanding of the Relationship Between Subjective Wellbeing and Eudaimonic Wellbeing Indicators in Adolescence

Toward an Understanding of the Relationship Between Subjective Wellbeing and Eudaimonic Wellbeing Indicators in Adolescence

Abigail Liza Mottershaw

August 2018

School of Psychological Science

A dissertation submitted to the University of Bristol in accordance with the requirements for award of the degree of Doctor of Philosophy in the Faculty of Life Sciences

Word count: 59,260

Abstract

Subjective wellbeing and eudaimonic wellbeing collectively assess wellbeing as an overarching construct. Yet investigation into the relationship between subjective wellbeing and diverse eudaimonic wellbeing indicators has so far been limited to a few studies with few eudaimonic wellbeing indicators. Little is known about how subjective wellbeing and eudaimonic wellbeing are related in adolescence, which is a critical developmental stage. I explored the relationship between subjective wellbeing and a diverse range of positive traits to capture eudaimonic wellbeing, including: the basic psychological needs, gratitude, optimism, trust, meaning in life, hopefulness, ambition, grit, curiosity and subjective health. I aimed to understand which positive traits were best considered as components of wellbeing and which traits were correlates of wellbeing, and identify the general and specific effects across subjective and eudaimonic wellbeing indicators.

I applied multivariate genetic analyses combined with principle components analysis to understand the aetiological relationship between subjective wellbeing and diverse eudaimonic wellbeing indicators in adolescence. My findings suggest that wellbeing was best characterised as an overarching construct with components of subjective wellbeing and eudaimonic wellbeing indicators, which largely share genetic influences. I also identified the positive traits that were best considered correlates, rather than components of wellbeing, reinforcing the need for a clear definition of wellbeing.

First using monozygotic twin analyses and second by measuring aspects of the physical environment, I also demonstrated that there are multiple environmental influences on subjective and eudaimonic wellbeing in adolescence. It is likely there are many environmental influences on subjective wellbeing and eudaimonic wellbeing, each with small effects in the same way there are multiple genetic influences with small effects, but together can explain substantial proportions of variance. In this genomic era, we will benefit from more investigation of environmental exposures to explain more of the missing heritability and the missing environmentality of behavioural traits.

Acknowledgements

First, I would like to thank my supervisors, Dr Claire Haworth and Dr Oliver Davis for their all of their support, encouragement and guidance throughout my PhD. You have given up so much time to support me and you have gone beyond your roles as supervisors, and for that I am so grateful.

Thank you to the wellbeing girls – Robyn and Adele. I feel privileged to have done my PhD alongside you both and I am forever grateful for your friendship. Thank you also to all the other PhD students I have met along the way – I am lucky to have made great friends. It has been such a great experience to share an office with you all and I will miss our afternoon coffee and cake motivation!

My research would not have been possible without the TEDS families giving up their time and energy to participate. I am also grateful for my PhD funding from the ESRC and the MRC and British Academy for funding the TEDS data collection.

Additionally, I need to thank my family and my friends outside of academia for all your support. Mum and Dad, you have helped me believe in myself and have the determination to push through until the end. Bec, Jessie and Briony, I would not have completed my PhD without your unwavering encouragement. You were all there for me constantly, and I can't thank you enough. And finally, Pete, thank you for your encouragement throughout but especially during my final year. You provided the support, motivation and distraction I needed.

Author declaration

I declare that the work in this dissertation was carried out in accordance with the requirements of the University's Regulations and Code of Practice for Research Degree Programmes and that it has not been submitted for any other academic award. Except where indicated by specific reference in the text, the work is the candidate's own work. Work done in collaboration with, or with the assistance of, others, is indicated as such. Any views expressed in the dissertation are those of the author.

SIGNED: .... DATE:.........................

Table of Contents

List of Tables

List of Figures

List of Appendices

List of Abbreviations

A	Additive genetic influences
ADHD	Attention deficit hyperactivity disorder
BMI	Body Mass Index
C	Shared environmental influences
CI	Confidence interval
COMPAS-W	Wellbeing scale (Composure; Own-Worth; Mastery; Positivity; Achievement; Satisfaction; Wellbeing)
D	Non-additive genetic influences
DNA	Deoxyribonucleic acid
E	Nonshared environmental influences
GCSE	General Certificate of Secondary Education
GE	Genotype-environment interplay
h^2	Heritability estimate
M	Mean
MR	Mendelian Randomisation
MSLSS	Multidimensional Student Life Satisfaction Scale
MZ	Monozygotic
NSE	Nonshared environmental influences
ONS	Office for National Statistics
OS	Ordnance Survey
PCA	Principal components analysis
rA (or rG)	Additive genetic correlation

RCT	Randomised control trial
rDZ	Correlation between DZ twin pairs
rE	Nonshared environmental correlation
rMZ	Correlation between MZ twin pairs
SSGAC	Social Science Genetics Association Consortium
SWB	Subjective wellbeing
TEDS	Twins Early Development Study
V	Variance
WB	Wellbeing
WHO	World Health Organisation

Chapter 1. Defining wellbeing

In psychological research there is no consensus on how wellbeing should be defined or measured. The aim of this chapter is to introduce and evaluate current psychological approaches to the study of wellbeing, with a particular focus on wellbeing in adolescence. In this chapter I first introduce the philosophical and psychological definitions of wellbeing. Next, I evaluate the current methods of assessing wellbeing. I then briefly present the often-studied correlates of wellbeing and address the importance of investigating wellbeing in adolescence. Finally, I outline the aims of this thesis and state the novel contribution to the scientific knowledge of wellbeing.

1.1 Defining wellbeing

There are two main philosophical definitions of wellbeing: *hedonic wellbeing* and *eudaimonic wellbeing*. These definitions have been operationalised for empirical investigation. Within the scientific research on wellbeing, it is widely accepted that hedonic wellbeing is operationalised as *subjective wellbeing*. The scientific study of eudaimonic wellbeing lacks a clear operational definition, though *psychological wellbeing* is the most prominent. More recently, the study of wellbeing has bridged the distinct philosophical distinctions and combined subjective wellbeing with eudaimonic wellbeing. The relationship between the philosophical and psychological definitions of wellbeing are summarised in Figure 1.1.

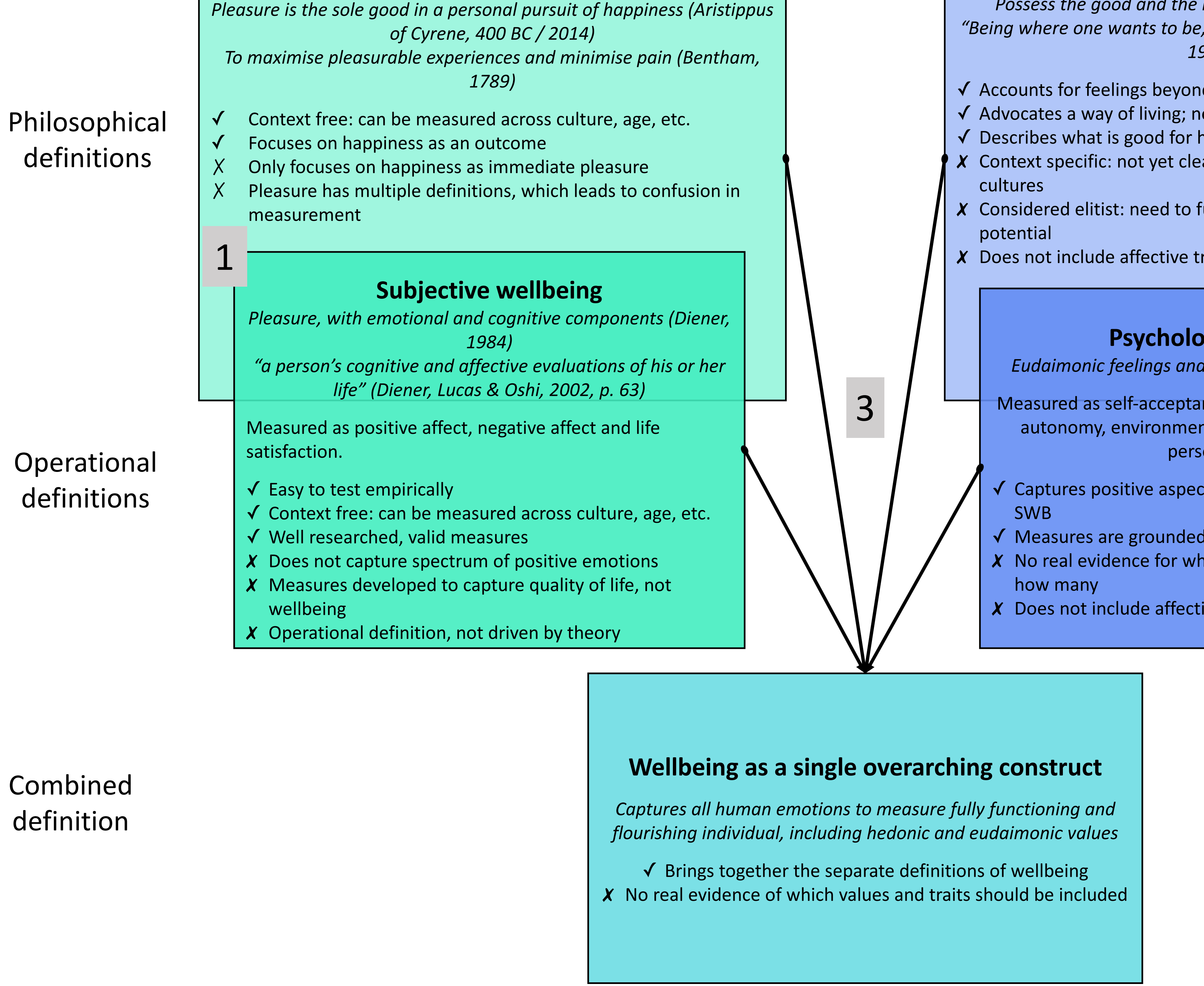


Figure 1.1 A visual representation of the relationship between the two main theoretical definitions of wellbeing (hedonic wellbeing and eudaimonic wellbeing psychological wellbeing), and a combined definition (wellbeing as a single overarching construct). A brief definition (given in italics), the strengths (✓) and

1.1.1 Philosophical definitions of wellbeing

1.1.1.1 Hedonic wellbeing

Hedonism is defined as happiness in the physical sense of pleasure, where a life that is full of immediate pleasures would amount to a happy life (Aristippus of Cyrene , 400 BC/2014). The 'complete theory of hedonism' aims to maximise happiness, and later became known as the 'principle of utility' (Bentham, 1789/1996). The 'principle of utility' promotes behaviours that increase present happiness and condemns behaviours that hinder present happiness from individualistic and societal perspectives (Bentham, 1789/1996). Hedonism does not account for sacrificing immediate gratification for pursuing goals, because the purpose of life is to enjoy living in the current moment.

Hedonic wellbeing has developed from Hedonism as the subjective pursuit of pleasure (Huta, 2016; Kubovy, 1999). It also requires a cognitive judgement on whether an individual's current actions will produce pleasure (Ryan & Deci, 2001). Consequently, hedonic wellbeing is defined as the physical sense of pleasure and a cognitive evaluation that you are living a pleasurable life. Empirical research began exploring feelings of hedonic happiness (emotion) in the 1920s (Beckham, 1929; Chassell, 1928), which led to the development of elation-depression scales (Jasper, 1930; Wessman & Ricks, 1966; Wilson, 1967). Positive affect was quickly recognised as distinct from negative affect (Bradburn, 1969), and research into hedonic wellbeing, including both affect and the cognitive judgement of achieving pleasure, emerged soon after (Andrews & Withey, 1976). This research field developed into subjective wellbeing (Diener, 1984) and the term hedonic wellbeing is rarely used in scientific research (Waterman, 2008).

1.1.1.2 Eudaimonic wellbeing

Plato taught that the happy life was one which possessed what is most valued (Plato, 380BC/1992). His student Aristotle extended this to mean the good and the beautiful (Aristotle, 350BC/2002), where the chief good is an activity that promotes excellence and leads to eudaimonia (Rowe & Broadie, 2002). Eudaimonia is a combination of 'eu', meaning good or healthy and 'daimon', meaning the true self (Waterman, 2013a). Eudaimonic wellbeing is considered as self-realisation (Goldstein, 1951; Maslow, 1970; Rogers, 1946, 1961). When achieved, it is the "essence of life itself" (Rogers, 1961) because the self is truly expressed (Sheldon, 2002). This moves beyond pleasure as an outcome, and focuses on a way of living that fits with individual intrinsic motivations to do what is worth doing: what is worth pursuing, worth conserving, and worth regretting the lack of (Rowe & Broadie, 2002).

It has been argued that eudaimonic wellbeing is a desired state but does not represent happiness (Diener, 1984). This depends on the definition attributed to happiness. Happiness has stemmed from both Hedonia and Eudaimona and therefore alternates between seeking pleasure and purpose (Tatarkiewicz, 1976). Happiness based on hedonism seeks pleasure in the present moment, sought by the many, according to Aristotle (350BC/2002) and corresponds with society's definition (Diener, Oishi, & Lucas, 2003). However, hedonic wellbeing is often criticised as being too simplistic to capture human experience and the development of human potential (Vittersø, 2013). In contrast, eudaimonic wellbeing will seek value and meaning and may not always bring happiness in the present moment. However, it is possible to experience Eudaimonia and Hedonia simultaneously (Waterman, 2013a). Eudaimonia is pursued by the wise, according to Aristotle (350BC/2002), and is criticised as being the definition of happiness provided by experts (e.g. philosophers and psychologists) instead of society (Diener, Sapyta, & Suh, 1998).

The difference between hedonic and eudaimonic wellbeing is particularly important when considering wellbeing in adolescence. Adolescence is a key developmental stage renowned for risky behaviours (Blakemore & Choudhury, 2006), where short term desires are prioritised over long term goals. Consequently, hedonic wellbeing (seeking pleasure) may be prioritised by adolescents over a eudaimonic wellbeing of seeking purpose. There is some evidence that hedonic wellbeing is experienced more frequently than eudaimonic wellbeing in adolescence (Keyes, 2006), and that younger adolescents are less orientated towards future goals compared to older adolescents and young adults (Steinberg et al., 2009). However, more research is needed to understand the relationship between hedonic and eudaimonic wellbeing in adolescence.

1.1.2 Definitions of wellbeing for empirical investigation

1.1.2.1 Subjective wellbeing

Subjective wellbeing is largely considered a synonym for hedonic wellbeing, but with a clearer operational definition (Waterman, 2008). Additionally, it can be partly traced to a Democritus philosophy, where a happy life is the best possible life, and to Aristippus of Cyrene's ethics (Tatarkiewicz, 1976). It relies on a state of mind and is therefore a subjective interpretation of happiness (Brancacci & Morel, 2007). According to Diener (1984), subjective wellbeing has roots in Stoic philosophy, where happiness is dependent on self-assessment (Aurelius, 180/2013). Consequently, subjective wellbeing relies on an individual's evaluation of whether they lead a happy life (Diener, 1984).

The scientific structure of subjective wellbeing, established over 40 years ago (Andrews & Withey, 1976), consists of three components: high positive affect, low negative affect, and high satisfaction with life, often referred to as the tripartite model (Diener, 1984). However, there is little agreement on how these components are structured (Busseri & Sadava, 2011). There are four prominent models across the literature: treating the three components as separate aspects of subjective wellbeing (Andrews & Withey, 1976; Diener, 1984; Diener & Lucas, 1999); assuming a hierarchical model where the three components represent a single latent factor of subjective wellbeing (Diener, Diener, & Diener, 1995; Lohmann, 1977; Sheldon & Lyubomirsky, 2006; Suh, Diener, Oishi, & Triandis, 1998); assuming a composite model where the three components cause subjective wellbeing (Busseri & Sadava, 2011); and specifying a causal relationship, where positive affect and negative affect contribute to overall life satisfaction (Schimmack, Diener, & Oishi, 2002). These models are summarised in Figure 1.2.

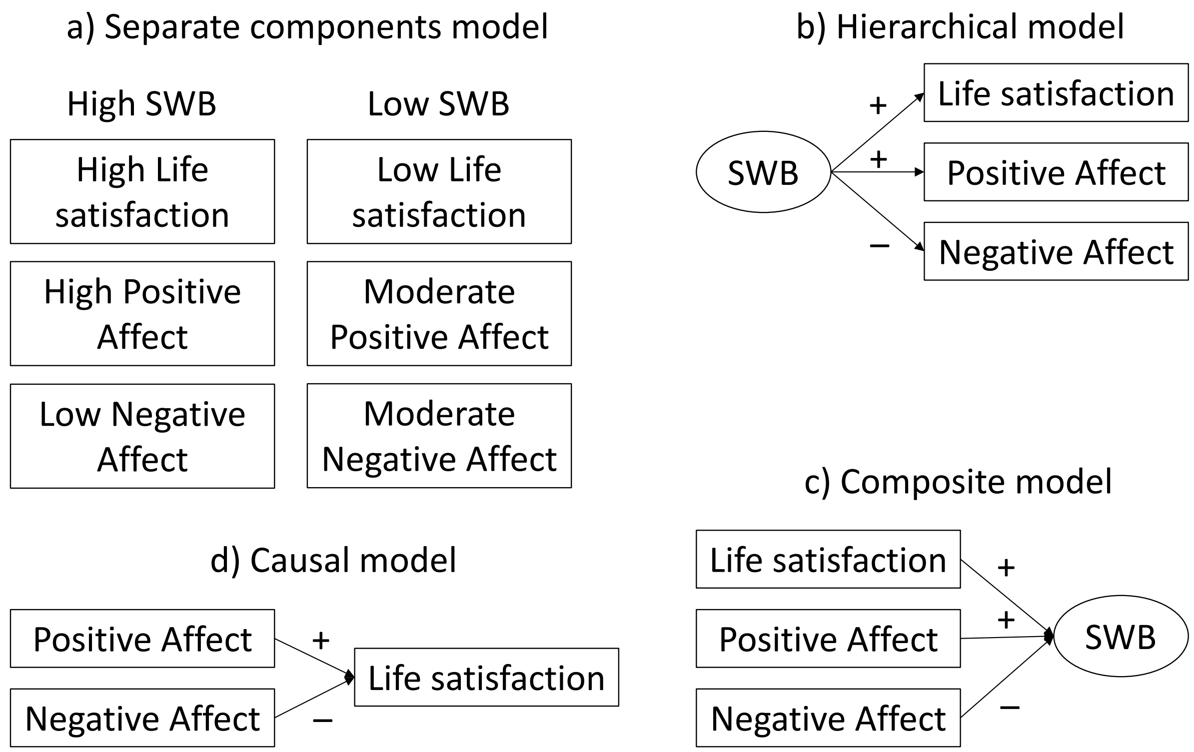


Figure 1.2 The different tripartite models of subjective wellbeing (SWB). a) The separate components model assumes that subjective wellbeing is attributed to life satisfaction, positive affect and negative affect, where high subjective wellbeing (SWB), is high life satisfaction, high positive affect and low negative affect, and low subjective wellbeing is low life satisfaction, moderate positive affect and moderate negative affect (Diener, 1984; Andrews & Whithey, 1976; Diener & Lucas, 1999). b) The hierarchical model assumes that subjective wellbeing is a latent factor, represented by the observed components of life satisfaction, positive affect and negative affect (Lohmann, 1977; Sheldon & Lyubomirsky, 2006; Suh et al., 1998; Diener, Diener & Diener, 1995). c) The composite model assumes that life satisfaction, positive affect and negative affect causally contribute to subjective wellbeing (Busseri & Sadava, 2011). d) The causal model specifies that positive affect and negative affect determine life satisfaction, which represents subjective wellbeing (Schimmack et al., 2002). The signs on the arrows represents the positive (+) and negative (–) contribution of the component to subjective wellbeing. The most plausible model appears to be the hierarchical model (Busseri, 2018).

A recent meta-analysis concluded that a hierarchical structure is most supported based on the correlations between the three components (Busseri, 2018). Yet the structure of the tripartite model is poorly grounded in theory and subjective wellbeing is therefore criticised as defined mostly by the way it is measured (Ryff, 1989). However, it has been argued that subjective wellbeing supports the way that society defines happiness (Diener, Oishi, et al., 2003), and has deep philosophical roots (Diener et al., 1998).

1.1.2.2 Psychological wellbeing and the scientific study of eudaimonic wellbeing

Much literature across the 20th Century explored positive psychological functioning, including the study of meaning in life (Jung, 1939); positive mental health (Jahoda, 1958); positive qualities (Allport, 1961); fully functioning individuals (Rogers, 1961); self-actualisation (Maslow, 1968); and tendencies for human fulfilment (Buhler & Massarik, 1968). This research had little impact on the scientific study of wellbeing, probably because it was not studied as components of the same overarching construct. Empirical research explicitly exploring eudaimonic wellbeing is relatively young (Waterman, 2008). A measure of psychological wellbeing (Ryff, 1989) has become popular to operationalise eudaimonic wellbeing, though there is no evidence that this measure captures all aspects of eudaimonic wellbeing. As a result, other researchers explicitly model eudaimonic wellbeing which leads to ambiguity.

Based on Eudaimonia, defined as living in accordance with one's true potential (Waterman, 2013b), psychological wellbeing was developed to model the values, strengths and characteristics of optimal functioning that extend beyond subjective wellbeing (Ryff, 1989). The model of psychological wellbeing has six dimensions: self-acceptance, positive relations with others, autonomy, environmental mastery, purpose in life and personal growth (Ryff, 1989). Empirical support of this six-dimensional structure is mixed (Burns & Machin, 2009; Ryff & Keyes, 1995; Springer & Hauser, 2006; Springer, Hauser, & Freese, 2006; Van Dierendonck, 2004). Generally, psychological wellbeing has provided a strong argument that wellbeing is more than hedonic feelings, but there is not enough evidence that these specific traits alone represent eudaimonic wellbeing. Consequently, other researchers have provided their own definitions of eudaimonic wellbeing. Self-determination theory suggests that eudaimonic wellbeing is experienced when the basic psychological needs of autonomy, competence and relatedness are fulfilled (Ryan & Deci, 2001), though the basic psychological needs could instead represent antecedents of wellbeing (Doyal & Gough, 1984; Ryan, Curren, & Deci, 2013). Eudaimonic wellbeing has also been defined as an overarching construct with components of psychological wellbeing, the basic psychological needs, and social support (Diener et al., 2009; Diener, Wirtz, et al., 2010). Across the literature, each definition of eudaimonic wellbeing includes a unique combination of psychological traits which makes empirical investigation of eudaimonic wellbeing ambiguous.

The positive psychological traits often considered as components of eudaimonic wellbeing include meaning and purpose (Ryff, 1989; Seligman, 2002); mastery, competence and engagement (Csikszentmihalyi & Csikszentmihalyi, 1992; Ryff, 1989); optimism (Selgiman, 2002); and self-acceptance (Maslow, 1968; Ryff, 1989). However, the inclusion of these traits over other positive psychological traits is not clearly justified. Philosophically, gratitude was considered the ultimate virtue (Cicero, 55/1877) and has been empirically explored as an aspect of wellbeing (Wood, Joseph, & Linley, 2007), but has not been explicitly included in a model of psychological or eudaimonic wellbeing. Furthermore, both subjective and eudaimonic wellbeing are arguably important to a life worth living. This is reflected in the transition towards defining wellbeing as a combination of subjective and eudaimonic wellbeing.

1.1.2.3 Combining subjective and eudaimonic wellbeing: reaching a multidimensional definition

In 2000, a special edition of the American Psychologist outlined the framework for positive psychology to encourage research on positive experience and personality (Seligman & Csikszentmihalyi, 2000). Though this is not the first call to focus on positive psychology (Allport, 1961; Jahoda, 1958), it was the first to gain ground in positioning positive psychological research as an independent field (Csikszentmihalyi, 2003). Positive psychology is the study of three kinds of positive life: the pleasant life, the good life, and the meaningful life (Seligman, 2002). This symbolises the move towards measuring different types of wellbeing simultaneously and the need for a collective approach to wellbeing was soon recognised (Biswas-Diener et al., 2009; Kashdan et al., 2008). This has encouraged scientific investigation into whether subjective wellbeing and eudaimonic wellbeing are components of one overarching construct.

Studies of hedonic and eudaimonic wellbeing have shown the two philosophical theories are complementary (for review, see Kashdan, Biswas-Diener, & King, 2008). Across the literature, measures of subjective wellbeing and psychological wellbeing correlate strongly (0.59 to 0.96: Keyes, Shmotkin, & Ryff, 2002; Linley, Maltby, Wood, Osborne, & Hurling, 2009), which suggests the two types of wellbeing are largely related. Research investigating the factor structure of subjective and psychological wellbeing have concluded that there is either one general factor (Disabato, Goodman, Kashdan, Short, & Jarden, 2016; Longo, Coyne, Joseph, & Gustavsson, 2016), or a two-factor structure to wellbeing (Keyes et al., 2002; Linley et al., 2009) that supports wellbeing as an overarching construct with hedonic and eudaimonic components. There is evidence of discriminant validity between subjective and psychological wellbeing (Disabato et al., 2016), and between the components of subjective wellbeing (Lucas, Diener, & Suh, 1996). The traits used to measure subjective and psychological wellbeing only show moderate correlations with each other (0.19 – 0.50, Keyes et al., 2002; 0.22 – 0.63, Disabato et al., 2016), suggesting that each component of subjective wellbeing and eudaimonic wellbeing capture distinct aspects of overall wellbeing. Together, this research supports the definition of wellbeing as an overarching construct that encompasses different types of wellbeing.

However, experimental investigation into the factor structure of wellbeing has so far been limited to a few studies with specific scales. Subjective wellbeing is often represented by life satisfaction, positive affect and negative affect and psychological wellbeing is usually measured using Ryff's six-dimensional scale (1989). More recent research has used diverse eudaimonic traits to assess the structure of wellbeing (Longo et al., 2016; Su, Tay, & Diener, 2014), yet there is no consistent way to conceptualise or measure the components of wellbeing as an overarching construct. As visualised in Figure 1.3, wellbeing has been conceptualised as represented by two components of subjective wellbeing and eudaimonic wellbeing (Diener, Wirtz, et al., 2010; Henderson & Knight, 2012; Waterman, 2008), but also as a single component of subjective wellbeing and multiple eudaimonic components

(Seligman, 2012; Su et al., 2014) and as multiple components of subjective and eudaimonic wellbeing (Keyes, 2002). It is important to reach a consistent conceptualisation of wellbeing because it impacts empirical investigation. For example, the prevalence of wellbeing across populations differs depending on the definition and measure of wellbeing (Hone, Jarden, Schofield, & Duncan, 2014). Though it is likely subjective wellbeing and eudaimonic wellbeing are caused by a shared underlying construct, we need more research that captures a diverse range of eudaimonic traits to truly understand the relationship between subjective and eudaimonic wellbeing and begin to identify the traits that can be considered as components of wellbeing.

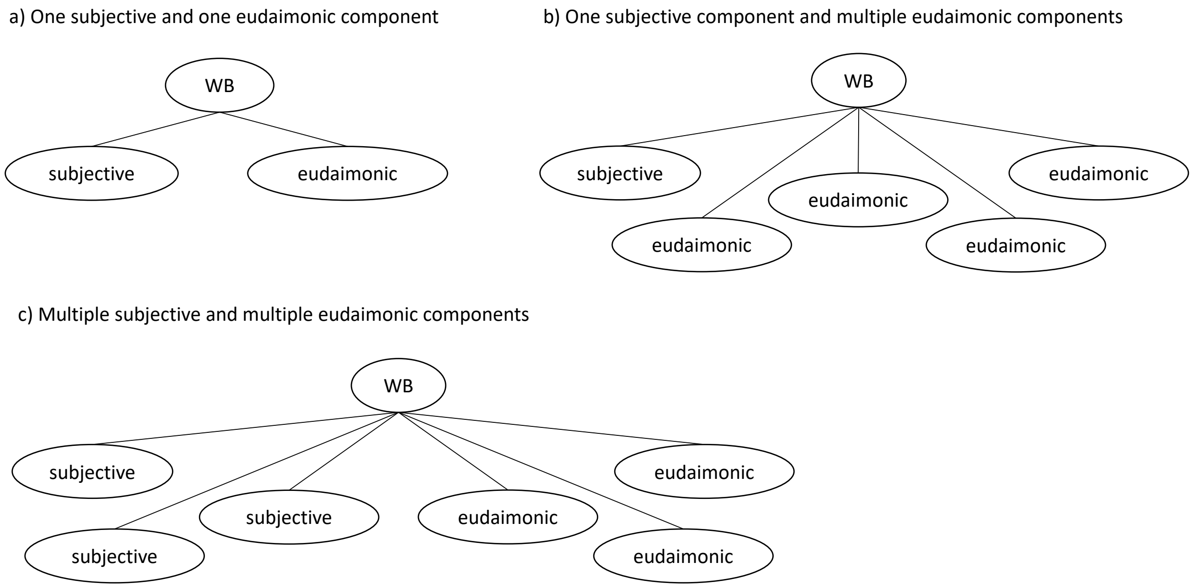


Figure 1.3 Three ways that wellbeing as an overarching construct has been conceptualised. a) Wellbeing is an overarching construct for subjective and eudaimonic wellbeing. b) Wellbeing is an overarching construct for subjective wellbeing and multiple components of eudaimonic wellbeing. c) Wellbeing is an overarching construct for components of subjective wellbeing and components of eudaimonic wellbeing.

1.1.3 Investigation of wellbeing in this thesis

In summary, hedonic and eudaimonic wellbeing have different philosophical definitions which are difficult to operationalise for scientific study. Subjective wellbeing and psychological wellbeing provide scientific definitions that can be measured accurately, though each has limitations. Subjective wellbeing is limited to measures of positive affect, negative affect and life satisfaction, and fails to capture positive functioning. Eudaimonic wellbeing attempts to capture positive functioning but the specific components are ambiguous. In this thesis I define wellbeing as a multidimensional construct, represented by components of subjective wellbeing and eudaimonic traits considered to capture positive functioning. By uniquely combining many diverse wellbeing indicators, I can achieve two outcomes. First, I can explore the relationship between the components of subjective wellbeing and more diverse eudaimonic traits. Second, I can assess the general and specific effects across subjective and eudaimonic wellbeing to understand the traits that constitute wellbeing and the traits that correlate with wellbeing.

1.2 Measuring wellbeing

Given the lack of a concrete definition of wellbeing, it is unsurprising there are many different measures of wellbeing both within psychology and wider scientific disciplines, as highlighted in previous reviews (Cooke, Melchert, & Connor, 2016; Lindert, Bain, Kubzansky, & Stein, 2015; McDowell, 2010; Linton et al., 2016; Charlemagne-Badal et al., 2015). The instruments used to measure wellbeing are diverse, and different reviews have grouped instruments into various categories. For example, Linton, Dieppe, and Medina-Lara (2016) report 99 instruments that span six distinct themes of wellbeing (mental wellbeing, social wellbeing, activities and functioning, physical wellbeing, spiritual wellbeing, personal circumstances). In contrast, Lindert et al., (2015) included 60 instruments that were reported to cover 25 distinct domains of wellbeing (the most frequent were affect, social relations, life satisfaction and physical health). However, these reviews fail to convey how instruments designed to capture wellbeing specifically relate to subjective and eudaimonic wellbeing. Only one review attempted to categorise measures using hedonic and eudaimonic perspectives, but the categories were much broader and included quality of life and wellness as types of wellbeing (Cooke et al., 2016). As there are different antecedents, correlates and outcomes of wellbeing depending on the type of wellbeing measured (Bolier et al., 2013; Ryff, Singer, & Love, 2004; Siedlecki, Salthouse, Oishi, & Jeswani, 2014; Wang, Davis, Wootton, Mottershaw, & Haworth, 2017), it is important we understand how the different wellbeing instruments represent subjective and eudaimonic wellbeing.

Consequently, I performed a literature review to uncover the instruments designed to measure subjective wellbeing, eudaimonic wellbeing and both subjective and eudaimonic wellbeing. The details on the search strategy, inclusion criteria and search results are provided in Appendix 1.1. I identified 40 instruments as subjective wellbeing, eudaimonic wellbeing, or both subjective and eudaimonic wellbeing (for list, see Appendix 1.2). Here, I discuss the components of wellbeing represented within each type of wellbeing (summarised in Table 1.1) and evaluate individual instruments.

Table 1.1 Descriptions of the components identified for each type of wellbeing (subjective, eudaimonic, and multidimensional) among the wellbeing instruments displayed in Appendix 1.2.

Wellbeing type	**Component (number of measures within category)**	**Definition**
Subjective	Emotion/affect (10)	Measures that specifically capture affect or emotion
Subjective	Happiness (4)	Measures that specifically capture happiness
Subjective	Life/Domain Satisfaction (6)	Measures that specifically capture life satisfaction, either as a global construct or as satisfaction with life domains
Eudaimonic	Psychological (3)	Measures that capture psychological wellbeing, including values, strengths and characteristics of optimal functioning, but do not include subjective characteristics
Eudaimonic	Self-realisation (1)	Measures specifically aimed to capture self-realisation as a characteristic of eudaimonic wellbeing, but do not include subjective characteristics
Subjective and eudaimonic	Subjective wellbeing and eudaimonic wellbeing (8)	Measures that specifically measure affect, feelings, life satisfaction or subjective wellbeing and values, strengths or characteristics of optimal functioning
Subjective and eudaimonic	Wellbeing as flourishing (3)	Aim to capture success by including domains specifically focused on competence or accomplishment, as well as including both subjective and eudaimonic dimensions
Subjective and eudaimonic	General wellbeing (5)	Measure wellbeing as one broad, overarching construct that captures many domains of wellbeing, including both subjective and eudaimonic dimensions

1.2.1 The components of wellbeing identified

Within each definition of wellbeing (subjective, eudaimonic, or subjective and eudaimonic), the instruments were designed to measure specific wellbeing components, displayed in Table 1.1. Half of the 40 instruments measured subjective wellbeing. This emphasises the dominance of subjective wellbeing as a definition of wellbeing, which is perhaps driven more by the available instruments than theoretical perspectives on wellbeing. Subjective wellbeing was consistently divided into the tripartite model of subjective wellbeing (Diener, 1984), with measures of positive (and negative) affect and life satisfaction. As instruments measured both positive and negative affect together, and few instruments measured only positive affect, I grouped affect measures into one component. I also included happiness as a separate component of subjective wellbeing because these instruments specifically measured happiness rather than affect more generally. No instrument alone captured all components of subjective wellbeing, and it is clear that affect or happiness instruments are commonly combined with life satisfaction instruments to capture subjective wellbeing.

Four instruments capture eudaimonic wellbeing, which specifically assess the values, strengths and characteristics for optimal functioning but do not assess any component of subjective wellbeing. Interestingly, all four instruments are strongly related to theory and demonstrate clear reasoning for the scale design. Two instruments are not derived from eudaimonic philosophy (psychosocial inventory of ego strengths, Markstrom, Sabino, Turner, & Berman, 1997; child and adolescent wellness scale, Copeland, Nelson, & Traughber, 2010), but both contain components related to eudaimonic traits such as will, purpose, competence and wisdom. Furthermore, each component of eudaimonic wellbeing is measured separately; no eudaimonic instrument provides one total score of wellbeing.

However, there is no consistency in the components included in each instrument, which creates difficulties when comparing findings across studies of eudaimonic wellbeing.

Sixteen instruments combine both subjective and eudaimonic wellbeing. Seven instruments clearly combine subjective and eudaimonic wellbeing, three instruments aim to capture success (flourishing) by additionally including elements of competence or accomplishment, and a further five instruments also include components beyond subjective and eudaimonic wellbeing, such as physical wellbeing. Twelve measures provide a total wellbeing score that combines many components of wellbeing, which is convenient when aiming to capture a snapshot of wellbeing as an overarching construct. However, by combining the components of wellbeing into a single score, the nuance in the components is lost. Instead, ten instruments provide composite scores for each component of wellbeing (four of these instruments do not provide a single wellbeing score), which allows researchers to explore differences in the associations across different components of wellbeing and capture the complexity in the experience of wellbeing.

It is important to emphasise the variety of components of eudaimonic wellbeing across the instruments. Some components are included frequently, such as positive relations with others (included thirteen times), purpose or meaning in life (included eight times) and competence or mastery (included seven times). However, I identified 38 different eudaimonic components across the instruments that measure eudaimonic or subjective and eudaimonic wellbeing (Appendix 1.3). From a theoretical perspective, it is difficult to justify why some of these traits are included as components of wellbeing and other traits are rarely included. For example, optimism is only included on four instruments and gratitude is not included in any instrument. Clearly, the field of wellbeing needs a standardised approach to eudaimonic wellbeing.

1.2.2 Instrument characteristics

I was most interested in the components of wellbeing measured across the instruments, but I also found similarities and differences in their design. First, a large number of instruments (25%) rely almost entirely on previous instruments as justification to develop a new scale. For example, the Public Health Surveillance Well-Being Scale (Bann, Kobau, Lewis, Zack, & Thompson, 2012) was developed as a national indicator of wellbeing by reviewing and combing previous scales and did not address any theoretical definitions of wellbeing. This was particularly true for subjective wellbeing instruments, which emphasises the criticism that subjective wellbeing is defined more by the way it is measured than by theory (Ryff, 1989). Second, most instruments were composed of standard questions and response scales except one instrument that used an implicit association task (implicit overall wellbeing measure, Diaz, Horcajo, & Blanco Abarca, 2009) and one instrument that used open ended questions (Eudaimonic and Hedonic Happiness Investigation instrument, Delle Fave, Brdar, Freire, Vella-Brodrick, & Wissing, 2011). Qualitative data is useful to understand the subjective experience of wellbeing in more detail and could develop understanding of an individual's definitions of wellbeing. However, there is evidence that people are inaccurate at predicting the impact of events on their wellbeing (Wilson & Gilbert, 2005), suggesting that people may be inaccurate at describing their subjective experience of wellbeing.

Third, all instruments included in my review are self-reports and suffer from known confounders on wellbeing such as social desirability (Diener, 1998) and social comparisons

(Diener & Fujita, 1997). To overcome the issues with self-reports, instruments (not included in my review) have been developed that use experience sampling (Csikszentmihalyi, Larson, & Prescott, 1977; Kahneman, Krueger, Schkade, Schwarz, & Stone, 2004), implicit measures (Settanni & Marengo, 2015; Wang et al., 2012) and physiological measures (for summary, see Diener, Scollon, & Lucas, 2003). Experience sampling of wellbeing captures different information than global measures (Diener, Scollon, et al., 2003) but has been considered a more ecologically valid measure of wellbeing (Dolan, Kudma, & Testoni, 2017) because it is likely to more closely capture the lived experience of wellbeing. Implicit measures that gauge subjective wellbeing from the positive and negative words used in posts on social media may increase the ecological validity of wellbeing assessment (Schwartz et al., 2016). It is not clear that outward expression of wellbeing on social media accurately represents level of wellbeing and so far this method is not effective for detecting cultural differences (Smith et al., 2016). However, much progress is being made in this field and it is likely these implicit measures of wellbeing will soon be validated (Schwartz et al., 2016). Finally, physiological measures of wellbeing could also increase validity (Diener, Scollon, et al., 2003), such as measures of heart rate, heart rate variability, blood pressure, body temperature, skin conductance and brain activity. The most recent systematic review of wellbeing and biological factors concluded that physiological factors are critical to wellbeing (Dfarhud, Malmir, & Khanahmadi, 2014). Therefore, we need to further understand the complex relationship between biological mechanisms and positive traits to use physiological measures as indicators of wellbeing.

Finally, there is considerable variation in the reliability of the instruments (internal consistency ranged from 0.52 to 0.96; test-retest reliability ranged from 0.58 to 0.98), but most measures had reliability estimates above 0.65. All types of wellbeing had at least one measure with high reliability and reliability did not vary across type of wellbeing (range: subjective = 0.59 to 0.95; eudaimonic = 0.52 to 0.93; subjective and eudaimonic = 0.55 to 0.96; median: subjective = 0.86; eudaimonic = 0.84; subjective and eudaimonic = 0.83). A meta-analysis estimated that 42% and 52% of the test-retest reliability in affect and life satisfaction respectively was due to the influence of stable factors (Anusic & Schimmack, 2016) and similar estimates are reported from longitudinal analyses using both self-report and experience sampling instruments (Hudson, Lucas, & Donnellan, 2017). This emphasises the importance of time-specific influences on self-reported wellbeing and it is possible only enduring factors impact wellbeing (Nes, Røysamb, Tambs, Harris, & Reichborn-Kjennerud, 2006). Furthermore, the variation in the time frame captured by each instrument (e.g. wellbeing within the last month; or 'in general…') could cause differences in reports of wellbeing by including different time-specific influences. Shorter time frames are often considered to capture more state-like aspects of wellbeing, though this has been difficult to test (Anusic & Schimmack, 2016). Future research should aim to use reliable and validated instruments with consistent time-frames to capture subjective and eudaimonic wellbeing.

In this thesis, I address the limitations in measuring wellbeing by combining subjective and eudaimonic instruments. I measure subjective wellbeing using instruments of subjective happiness and life satisfaction and I measure eudaimonic wellbeing using instruments that capture 12 positive psychological traits. The instruments I used will be discussed in detail in Chapter 3.

1.2.3 Exclusion of instruments as measures of wellbeing

Many instruments did not meet my inclusion criteria (outlined in Appendix 1.1) because they were not referred to as a standalone measure of wellbeing, or they were focused on mental illness.

Many positive traits have been considered as components of eudaimonic wellbeing, such as optimism (Lawlor, Schonert-Reichl, Gadermann, & Zumbo, 2014) and meaning (Diener, Wirtz, et al., 2010; Ryff, 1989; Seligman, 2002). However, any instrument that measures only one of these eudaimonic traits does not itself capture the construct of eudaimonic wellbeing. This issue has been highlighted in previous reviews (Rose et al., 2017), and emphasises the problem of poorly defined eudaimonic components. In contrast subjective wellbeing is clearly defined (Diener, 1984) and any instrument that measures affect or life satisfaction measures a component of wellbeing. This may explain why there are more subjective instruments than eudaimonic instruments included in my review.

Many instruments considered to measure wellbeing were developed to measure quality of life or mental illness. For example, the World Health Organisation (WHO) instruments of quality of life (WHOQOL Group, 1994, 1998) have been used to measure wellbeing but focus more on physical health and a low score (below 13) on the WHO-5 wellbeing index (WHOQOL Group, 1998) indicates the need to test for depression. Other instruments attempt to capture the spectrum of mental health, from mental illness to flourishing (Keyes, 2002). However, subjective wellbeing is more than the absence of mental illness (Haworth, Carter, Eley, & Plomin, 2015). We need to use measures that truly capture the components of subjective and eudaimonic wellbeing.

It is also worth considering the degree of instrument refinement across the literature. Instrument refinement is used to improve psychometrics and scale performance. For example, psychometrically valid shortened versions of instruments are useful for large scale data collection where space or time is limited. However, continual refinement and renaming of instruments leads to a field of multiple instruments with very similar psychometric properties. For example, the general wellbeing schedule (Fazio, 1977), the psychological wellbeing index (Dupuy, 1984), and the psychological general wellbeing index – revised (Revicki, Leidy, & Howland, 1996) are almost identical and there are no recommendations on which version is preferred. There is also confusion when instruments are simply combinations of previous instruments (e.g. the mental health continuum, Keyes 2002), extensions of previous instruments with additional items (e.g. the extended satisfaction with life scale, Alfonso, Allison, Rader, & Gorman, 1996), or simply the same instrument renamed (e.g. the global happiness scale, Parackal (2016) is the subjective happiness scale Lyubomirsky & Lepper (1999). The scientific field of wellbeing needs to concentrate on defining wellbeing rather than developing additional measures.

1.2.4 Measuring wellbeing in adolescence

Assessing wellbeing in adolescence requires instruments that are age-appropriate and have been validated for use with adolescents. Of the 40 instruments identified in my literature review, only five were developed specifically for use with children and adolescents and two were adapted for use with adolescents. Few instruments capture subjective and eudaimonic wellbeing in adolescence; a recent systematic literature review identified only 11 instruments that could be used to assess wellbeing in adolescence (Rose et al., 2017) and only four were specifically developed for adolescence. Though all instruments had some evidence of validity for use with adolescents, only one instrument had been cognitively assessed with focus groups of adolescents for item comprehension and appropriateness (the Warwick-Edinburgh mental wellbeing scale, Clarke et al., 2011). It is incredibly important that instruments are assessed for appropriateness with adolescents to ensure that the instrument is effectively measuring wellbeing. I have addressed this by using age appropriate instruments (see Chapter 3 for further details).

1.2.5 Methodological considerations for phenotype equivalence

Given the diversity in wellbeing instruments, we need to consider how to assess their equivalence. Factor analysis is used to assess the assumption that different components of wellbeing have the same latent construct (Comrey & Lee, 2013). Discriminant validity is assessed by observing differences in the magnitude of correlations between different wellbeing components and other psychological traits. Theoretically, we would not expect all components of wellbeing to correlate equally with other psychological traits. For example, large differences have been observed in the association between income and life satisfaction compared to positive affect (Diener, Ng, Harter, & Arora, 2010). Currently, no research has explored the similarities and differences in the relationship between a diverse range of wellbeing components and other psychological traits.

Genetically informative designs allow exploration of the overlap in the aetiology of different wellbeing measures and uncover the extent to which the genetic and environmental influences on one component of wellbeing also influence another component of wellbeing. Finding considerable genetic overlap provides support for the idea that wellbeing is an overarching concept. Rarely is there complete genetic overlap between traits (Plomin, DeFries, Knopik, & Neiderheiser, 2013), suggesting some specificity, which might relate to distinct components, or might be driven by measurement error. To date, no research has applied these methods to a diverse set of wellbeing indicators collected in the same sample.

This thesis addresses these gaps in our understanding of wellbeing. Chapter 4 will address how components of subjective and eudaimonic wellbeing relate to each other, and to other psychological traits. And Chapter 5 will explore the aetiological relationship between diverse indicators of wellbeing.

1.3 Establishing the antecedents, correlates and outcomes of wellbeing

Wellbeing has been associated with many positive life outcomes (Lyubomirsky, King, & Diener, 2005), yet much research uses cross-sectional designs and correlational analyses. This makes it difficult to establish causation and it is not clear whether wellbeing is an antecedent, correlate or outcome for other important life outcomes. Furthermore, associations with wellbeing are dependent on the type of wellbeing indicator used, and there are specific associations observed with wellbeing in adolescence.

1.3.1 Establishing causal relationships with wellbeing

Literature reviews have established associations between wellbeing and successful life outcomes in domains such as health, relationships and work (Chu, Saucier, & Hafner, 2010; Diener, Pressman, Hunter, & Delgadillo-Chase, 2017; Lyubomirsky et al., 2005; Pressman & Cohen, 2005). One large meta-analysis tried to indicate causation by combining evidence from correlational, longitudinal and experimental studies (Lyubomirsky et al., 2005). They found robust evidence that subjective wellbeing was consistently associated with positive life outcomes across different study designs, suggesting that increases in subjective wellbeing are causally related to positive outcomes. However, correlational studies indicate the presence of a relationship and are not evidence of causation. Longitudinal studies show bidirectional relationships between subjective wellbeing and life outcomes including physical health (Diener et al., 2017), mental health (Fergusson et al., 2015; Zadow, Houghton, Hunter, Rosenberg, & Wood, 2017) and personality (Specht, Egloff, & Schmukle, 2013; Tauber, Wahl, & Schröder, 2016). This indicates that high subjective wellbeing may lead to positive life outcomes, but positive life outcomes may also lead to high wellbeing. We need to consider the dynamic interplay between wellbeing and other life outcomes to understand this complex relationship.

One way to establish causation is to use randomised control trials (RCTs), which randomly assign individuals to a treatment or control condition in order to measure the effect of an outcome. For subjective wellbeing, this could be achieved by conducting a wellbeing intervention as a proxy for higher wellbeing and testing the effect of randomly being assigned to an intervention or not on the outcomes of interest. However, randomised control trials can be costly and time consuming. An alternative which uses readily available data is Mendelian Randomisation. Mendelian Randomisation (MR) is a variation of instrumental variable analysis, where the genetic variant acts as an instrument for an exposure to test if there is a causal relationship with an outcome. If there is an effect of the exposure (e.g. physical health) on the outcome (e.g. wellbeing), we would expect the genetic variants for the exposure would be associated with the outcome, assuming that the only possible pathway from the genetic variant to the outcome is directly through the exposure (Davey Smith & Ebrahim, 2003).

MR has been used to explore the relationship between subjective wellbeing and physical health. However, only a higher BMI was causally associated with lower subjective wellbeing and there was no evidence that subjective wellbeing caused BMI and no relationship between subjective wellbeing and other physical health traits including level of cholesterol and coronary artery disease (Wootton et al., 2018). Furthermore, a causal association has been found between subjective wellbeing and eudaimonic wellbeing, but not the reverse (Baselmans & Bartels, 2018). However, these results should be interpreted with caution as they could also be explained by a lack of power to detect the effect of eudaimonic wellbeing on subjective wellbeing, or by violations in the MR method because of the similarity in the genetic architecture of the variables. The use of MR to understand causality in wellbeing is an exciting area for future research.

One issue when trying to establish causation is the definition of wellbeing, and the definition of positive life outcomes. The definition of eudaimonic wellbeing is a worthwhile life (Waterman, 2008), which is arguably equal to a successful life. It may not be possible to separate the behaviours and characteristics needed to live a successful life from those that represent eudaimonic wellbeing. For example, in the large meta-analysis of successful life outcomes, optimism is considered as both an indicator of wellbeing and as a characteristic of a successful life (Lyubomirsky et al., 2005). Furthermore, social relationships are considered as a positive outcome, yet positive relationships with others is often a component of eudaimonic wellbeing. We need to maintain a distinction between the components of wellbeing and potential correlates (Kashdan et al., 2008). It is essential to provide a clear and consistent definition of wellbeing, or it will be impossible to establish the correlates of wellbeing.

1.3.2 Differences in the correlates of wellbeing across wellbeing indicators

Differences in the relationship between specific components of wellbeing and the correlates of wellbeing highlight the need to measure both subjective and eudaimonic wellbeing when conducting wellbeing research. Subjective and eudaimonic wellbeing indicators have shown different associations with a range of healthy biomarkers (Ryff et al., 2004), social support measures (Siedlecki et al., 2014; Wang et al., 2017) and mean effect sizes in response to interventions (Bolier et al., 2013). Furthermore, the components of subjective wellbeing show different associations with income (Diener, Ng, et al., 2010) and physical health (Gana et al., 2016; Howell, Kern, & Lyubomirsky, 2007; Skaff et al., 2009). Multiple types of wellbeing should be measured simultaneously to capture the nuance in the antecedents, correlates and outcomes of wellbeing.

1.3.3 Correlates of wellbeing in adolescence

Socio-demographic factors explain little variation in wellbeing in adolescence (Bradshaw, Keung, Rees, & Goswami, 2011; Dinisman & Ben-Arieh, 2016; Klock, Clair, & Bradshaw, 2014). Stronger associations are observed between adolescent subjective wellbeing and factors including peer and parental relationships (Oberle, Schonert-Reichl, & Zumbo, 2011; Wang et al., 2017), school engagement (Lewis, Huebner, Malone, & Valois, 2011), the school environment (Kidger, Araya, Donovan, & Gunnell, 2012) and personality (Anglim & Grant, 2014). Consistent with adult samples (Lyubomirsky et al., 2005; Rohrer, Richter, Brümmer, Wagner, & Schmukle, 2018), the relationship between wellbeing and social relationships in adolescence is one of the most robust findings.

Higher levels of perceived parental involvement are positively associated with subjective wellbeing (for review, see Cripps & Zyromski, 2009), but peers are a more important source of support than parents during adolescence (Furman & Buhrmester, 1992). Peer friendships are positively associated with subjective wellbeing (Balluerka, Gorostiaga, Alonso-Arbiol, & Aritzeta, 2016; Tomé, de Matos, Camacho, Simões, & Diniz, 2014), where friendship quality and authenticity are most important (Chu et al., 2010; Peets & Hodges, 2017; Wang et al., 2017). Furthermore, negative experiences with peers have a large negative effect on subjective wellbeing (Rigby, 2000), though perceived social support can mitigate this (Arslan, 2017; Davidson & Demaray, 2007). These associations are largely correlational and most research uses subjective wellbeing indicators. Further research should explore the relationship between social relationships and wellbeing using diverse indicators. This will be addressed in chapters 4 and 6 of my thesis.

1.4 Wellbeing in adolescence

The UK government advocates the need to promote good wellbeing and mental health and prevent poor mental health to allow people to lead better lives (Mental Health Taskforce, 2016). However, official UK statistics on the status of mental health in adolescence are vastly out of date and largely concentrate on negative mental health outcomes. Though negative mental health outcomes, such as anxiety or depression, and wellbeing are distinct constructs they are also highly correlated both phenotypically and genetically (Bartels, Cacioppo, van Beijsterveldt, & Boomsma, 2013; Haworth et al., 2015). This suggests that there is much overlap between negative mental health outcomes and wellbeing and statistics on the current state of mental illness in adolescence gives some indication on the state of adolescent wellbeing. The next UK Child and Adolescent Mental Health Survey is due to be published this year. The current survey, published in 2004, found 10% of young people aged 5 to 16 years had a clinically diagnosed mental disorder (Green, McGinnity, Meltzer, Ford, & Goodman, 2004). Similarly, the Children's Society reported that 82% of children were flourishing in 2014, defined as having high subjective and eudaimonic wellbeing, 8% had high subjective or high eudaimonic wellbeing, and 10% had low subjective and eudaimonic wellbeing (The Children's Society, 2016). Subjective wellbeing in adolescence rose in the UK between 2002 and 2009 (Bradshaw, Martorano, Natali, & de Neubourg, 2013) but has declined in the UK across the years 2009 to 2014, particularly overall life satisfaction and satisfaction with appearance (The Children's Society, 2017). We need to understand more about the factors that influence wellbeing in adolescence to prevent the trend of decreasing adolescent wellbeing. Furthermore, the majority of mental health issues first occur in adolescence and 75% of all mental health disorders occur by the age of 25 (Kessler et al., 2007). Wellbeing in adolescence predicts wellbeing in adulthood (Coffey, Warren, & Gottfried, 2014), emphasising the future effects of adolescent mental health on our working population and the future NHS. We need to build our knowledge of how to tackle this crisis and both prevent mental illness and improve wellbeing and mental health in adolescence.

The slow decrease in subjective wellbeing and substantial rise in mental health disorders reported by young people (Rutter & Smith, 1995; The Children's Society, 2017; Williams et al., 2015) could be due to increased reporting in later cohorts for reasons such as changes in diagnostic criteria, assessment methods or official reporting practices (Bor, Dean, Najman, & Hayatbakhsh, 2014; Collishaw, Maughan, Goodman, & Pickles, 2004). Epidemiological data suggests there is considerable stability over time in overall levels of mental illness (Bor et al., 2014; Lessof, Ross, Brind, Bell, & Newton, 2016). However, there are consistent reports of increased mental health issues and decreased life satisfaction in adolescent girls and mixed evidence for adolescent boys (Bor et al., 2014; Edbrooke-Childs, Deighton, & Wolpert, 2017; Lessof et al., 2016; The Children's Society, 2017). The gender difference in satisfaction with life as a whole and with appearance is getting larger (The Children's Society, 2017), suggesting that adolescent girls are becoming less happy than adolescent boys. This is unlikely to be due to methodological confounders because it is a specific finding that does not consistently replicate in samples of boys, children or toddlers (Bor et al., 2014). Possible explanations include decreased perception of control over future employment prospects, increased family conflict, and increased pressure from social media (Lessof et al., 2016; Bor et al., 2014). However, we are yet to fully understand the environmental factors that cause increased mental health problems in both adolescent girls and boys.

To improve wellbeing in adolescence and inform possible interventions, we need to understand what constitutes wellbeing. First, this can be addressed phenotypically by assessing the correlates of diverse wellbeing components. This may uncover which wellbeing components are most appropriate for specific interventions. For example, if the aim is to improve wellbeing in a social context, then we should target wellbeing components that are most associated with social support or social relationships. Alternatively, if the aim is to improve wellbeing for increased productivity, then we should target wellbeing components that are most associated with learning and achievement. Second, genetically informative study designs can inform our understanding of wellbeing in adolescence by providing estimates of the similarities and differences in the genetic and environmental aetiologies of diverse wellbeing indicators. We can then understand which wellbeing traits are more genetically similar, and which traits may be better considered as correlates of wellbeing.

1.5 Thesis aims

In this thesis, I aimed to understand how subjective and eudaimonic wellbeing components are related, and to explore the impact of specific environments on wellbeing in adolescence. This thesis contributes to scientific knowledge in a novel way for four reasons. First, we assess subjective wellbeing along with a diverse range of eudaimonic traits in an attempt to understand what traits constitute overall wellbeing. Second, we use genetically informative study designs to identify the genetic and environmental influences on each wellbeing component and the similarities and differences between the components. This analysis has never been conducted using such a diverse range of wellbeing indicators. Third, we use an adolescent sample to explore wellbeing during this specific development period. Much more research is conducted in adults than adolescents, but adolescence is a crucial developmental period when most mental illnesses first occur (Kessler et al., 2007). Finally, we use novel approaches to understand the impact of specific environmental factors on wellbeing in adolescence, including a crowd-sourced dataset to assess the impact of the physical environment on wellbeing in adolescence.

I begin this thesis by investigating how subjective and eudaimonic wellbeing indicators are related to each other phenotypically in adolescence, and how they are related to other psychological traits (Chapter 4). Next, I investigate the genetic and environmental aetiologies of each of the wellbeing indicators and explore the aetiological similarities and differences between them (Chapter 5). I then use a genetically informative design to identify specific non-shared environmental influences on wellbeing in adolescence (Chapter 6), and finally demonstrate a novel method to assess the impact of specific aspects of the physical environment on subjective wellbeing in adolescence (Chapter 7).

1.6 Chapter Summary

This chapter has provided an overview of the current scientific knowledge on wellbeing from three broad areas of defining wellbeing, measuring wellbeing and understanding the correlates of wellbeing. The two distinct philosophical definitions of hedonic and eudaimonic wellbeing have led to operational definitions of subjective and psychological wellbeing. Subjective and eudaimonic wellbeing have more recently been measured collectively to assess wellbeing as an overarching construct, though there is no consistent structure for a definition of wellbeing with diverse components. A multitude of different instruments have been developed to capture wellbeing, yet most instruments lack strong theoretical justifications for the traits included as components of wellbeing. In this thesis, wellbeing is defined as an overarching construct consisting of components of subjective wellbeing and a diverse range of eudaimonic wellbeing indicators. Research has shown a variety of positive life outcomes are correlated with wellbeing (Diener et al., 2017; Lyubomirsky et al., 2005; Ryff, 2013), yet establishing causation is difficult and it is likely the relationship is bidirectional. It is incredibly important to address wellbeing in adolescence given the emergence of mental illness at this developmental stage and the current lack of scientific understanding on how to improve adolescent wellbeing.

Genetically informative studies can be used to investigate the aetiological relationship between diverse wellbeing indicators. Consequently, the next chapter will describe the field of quantitative genetics and the current estimates of the genetic and environmental influences that explain variation in wellbeing.

Chapter 2. Understanding variability in wellbeing

The previous chapter introduced wellbeing as an overarching construct. As shown, wellbeing has been difficult to define, with different definitions stemming from hedonic and eudaimonic philosophy. The scientific field of wellbeing has developed many different instruments to measure wellbeing, yet there is still no firm consensus on how wellbeing should be defined or measured. I have defined wellbeing as an overarching construct represented by subjective wellbeing and diverse indicators of eudaimonic wellbeing. Higher wellbeing has been associated with many positive life outcomes, yet most studies are correlational. More research is needed that uses genetically informative designs to explore the causes of variation in wellbeing. Consequently, part of my thesis uses genetically informative twin designs to explore the genetic and environmental contribution to the variation across diverse wellbeing indicators.

In this chapter, I introduce the research field of quantitative genetics. I aim to give an overview of quantitative genetic methods generally as well as the current knowledge of the heritability and environmental influences on wellbeing. I also aim to discuss the aetiology of adolescent wellbeing and emphasise why further research is needed in this area. Structurally, this chapter has two sections. The first describes quantitative genetics, the common methods of behavioural genetics and assumptions of these methods. It also explains the concepts of heritability and environmental influences, which are used in behavioural genetics. The second discusses previous research that has explored wellbeing using genetically informative designs, organised into the heritability of wellbeing and the environmental influences on wellbeing.

2.1 Quantitative and behavioural genetics

For every possible complex trait, we observe individual differences. Quantitative genetics aims to answer, "to what extent are the *differences* observed among people conditioned by the differences of their genotypes and by the differences between the environments in which people were born, grew and were brought up?" (Dobzhansky, 1964, p. 55). Using scientific research to estimate the importance of genetic and environmental influences on behaviours and disorders (Haworth & Plomin, 2010; Plomin, DeFries, Knopik, & Neiderheiser, 2013), quantitative genetics quantifies the proportion of variation in a trait which is attributable to genetic variation, referred to as heritability, and the proportion due to environmental variation.

2.1.1 Brief history of behavioural genetics

The inception of quantitative genetics can be traced back over 150 years. Inspired by Darwin's publication of *The Origin of Species* (1859), Galton was the first to theorise that variation in human behaviour was due to genetic influences based on family studies of eminent men (Galton, 1869, 1883). Galton developed methods of human quantitative genetics, including family, twin and adoption methods and the basic statistic of familial resemblance (Plomin & Craig, 1997). Though his paper using twin methodology is considered the first to describe the classical twin method (Galton, 1876), the biological mechanisms were not understood at the time (Bouchard & Propping, 1993; Liew, Elsner, Spector, & Hammond, 2005).

At the same time, molecular genetics began with Mendel studying inheritance in pea plants. He hypothesised that discrete units of heredity were passed on through each generation (1866; in Mendel, 1965). This led to research that attempted to find single-gene transmission patterns for distinct categorical phenotypes, such as blood type (Plomin, Haworth, & Davis, 2009). However, Galtonians believed that the laws of heredity could not be applied to more complex human traits, which are continuously normally distributed across a population (Plomin & Craig, 1997). These differences in thinking were reconciled by Fisher (1918), who extended Mendel's theory to complex traits, where many genes of small effect can cumulatively cause the observed pattern of normal distribution. Yet research in quantitative and molecular genetics remained largely separate: quantitative genetics aimed to establish the overall effect of genetic and environmental influences on trait variation, whereas molecular genetics investigated the specific genetic variants that contribute to trait variation. Within the last three decades, these distinct fields have come together to explore the aetiology of complex traits (Plomin & Craig, 1997).

Behavioural genetics uses both quantitative and molecular genetic methods to understand the genetic and environmental influences on complex traits (Plomin et al., 2013). The modern era of behavioural genetics stems from Fuller and Thompson's book, *Behavior Genetics* (1960). It has been estimated there were 36,800 behavioural genetic publications since the publication of *Behavior Genetics* until 2014, where the number of publications increased substantially per year (Ayorech et al., 2016). Publications span most of the behavioural sciences, though far more publications use molecular genetics methodology than quantitative methodology and less than 3% combine molecular and quantitative methods (Ayorech et al., 2016). This may indicate more interest or more demand for molecular genetic research compared to quantitative research.

However, there is value in quantitative genetics within the era of molecular genetics. Quantitative methods can inform molecular genetics of the traits that have substantial genetic influences and are worth exploring at a molecular level (Plomin & Craig, 1997), though molecular genetics so far has been unable to account for the degree of heritability found using quantitative methods, leading to missing heritability (Manolio et al., 2009). Quantitative methods also go beyond estimating proportions of genetic and environmental influences. It includes tests of environmental influences, changes in genetic and environmental influences across time, and similarities in genetic and environmental influences across traits (Haworth & Plomin, 2010). It is anticipated that quantitative genetics will continue to add value to molecular genetics research for some time (Plomin et al., 2013).

Though behavioural genetics uses both quantitative and molecular genetic methods, this thesis is focused on quantitative methods. Consequently, I will briefly describe the common methods used in quantitative genetics, and then focus on the study designs that I have used in this thesis.

2.1.2 Methods in quantitative genetics

Quantitative genetics aims to decompose the proportion of variation in a trait into genetic and environmental influences (Plomin et al., 2013). For almost all human traits, we consistently find that genetic influences explain a substantial proportion of the variation

(Polderman et al., 2015). In human studies, quantitative genetics methods rely on naturally occurring genetic and environmental variation and use family, twin and adoption data or a combination of these study designs (Rijsdijk & Sham, 2002). The findings that genetic influences substantially contribute to trait variation replicates across the different study designs (Plomin & Craig, 1997). Family studies (for example, parent-offspring or sibling designs) cannot alone untangle the relationship between nature and nurture (Plomin & Craig, 1997), but they provide an estimate of family resemblance. As a result, twin and adoption studies are used much more frequently.

2.1.2.1 Adoption studies

Adoption studies can disentangle genetic and environmental influences because genetically-related individuals are reared apart (e.g. biological parents and adopted-away offspring) and genetically-unrelated individuals are reared together (e.g. adoptee and their adoptive parents or adoptive siblings) (Plomin & Craig, 1997). Any correlation between the adoptee and their adoptive parents must be due to the shared environment. Any correlation between the adoptee and their biological parents must be due to genetic influences (Plomin et al., 2013). The first adoption study was conducted in 1924 (Theis, 1924) and the method became popular in the first half of the 20th century. However, the number of adoptions has declined over the past 50 years meaning there are fewer samples available for research (Plomin et al., 2013).

2.1.2.1.1 Assumptions of adoption studies

The adoption design has three major assumptions (Plomin et al., 2013). First, it is unclear whether adoptees are representative of the general population due to the circumstances with which adoptions occur. Some adoption cohort studies appear representative of the nonadoptive population (Petrill, Plomin, DeFries, & Hewitt, 2003) whereas other studies have shown limited representativeness (Stoolmiller, 1999). Second, the resemblance between biological mother and offspring may reflect prenatal influences rather than genetic influences. This could be tested by comparing estimates of similarity between the child and the biological mother with that of the biological father, but there are few samples with data available. Finally, selective placement inflates the similarity between an adoptee and their adoptive family members (due to higher genetic similarities) as well as the adoptee and their biological parents (due to higher environmental similarities). If placement selection is present, it should be accounted for within any statistical analyses.

2.1.2.2 Twin studies

Twin studies assume that identical (monozygotic, MZ) twins share 100% of their DNA, and non-identical (dizygotic, DZ) twins share on average 50% of their DNA that varies across individuals (Plomin et al., 2013). Twin studies also assume that both MZ and DZ twins share the environment that is common to family members (referred to as the *shared environment*) (Rijsdijk & Sham, 2002). Using this knowledge, it is possible to decompose the observed traits of twins into underlying genetic and environmental influences (Rijsdijk & Sham, 2002). As genetic influences and shared environmental influences are completely shared by MZ twins, anything that makes MZ twins different from each other must be due to environmental effects that are experienced by each twin uniquely (referred to as the *nonshared environment*). If MZ twins are more similar than DZ twins for a given trait, then genetic influences must contribute to the variation in the trait (Plomin et al., 2013). In this thesis, I focus on the twin method of quantitative genetics, which is explained in detail in Chapter 3.

The first twin study to quantify the influence of genetics was conducted in 1922 to investigate refraction in the human eye (Jablonski, 1922), and the first twin study on behavioural traits soon followed (Merriman, 1924). There are now a multitude of twin cohorts, with a meta-analysis in 2015 reporting there were more than 14 million twin pairs from 39 different countries used in published research since 1965 (Polderman et al., 2015). A vast range of human traits are studied using twin designs, with 17,804 traits explored using twin studies from 2,748 publications (Polderman et al., 2015).

2.1.2.2.1 Assumptions of twin studies

The assumptions in twin studies include: MZ and DZ twins share their environments to the same extent (the equal environments assumption); GE interplay is minimal for the trait being studied; there is no assortative mating; twins are generalizable to the population; the genetic similarity for MZ twins is 100% and for DZ twins is 50%; and that sharing or not sharing the chorion does not influence behavioural traits (Plomin et al., 2013; Rijsdijk & Sham, 2002). These assumptions have been tested and validated using various methods, including adoption designs (Plomin et al., 2013; Rijsdijk & Sham, 2002). Here, I will expand on the main assumptions of twin studies and the evidence of their validity.

Assumption 1: Equal environments assumption

The first assumption is that the environments causing similarity between MZ and DZ twin pairs are experienced to the same extent regardless of zygosity. This may be violated because MZ twins are more similar and therefore may experience more similar environments than DZ twins, inflating heritability estimates.

Empirical investigations support the equal environments assumption for most behavioural traits (Conley, Rauscher, Dawes, Magnusson, & Siegal, 2013). One method to test this assumption compares within twin pair correlations between correctly classified and misclassified MZ and DZ twins. The assumption would be violated if biological DZ twin pairs misclassified as MZ twin pairs show within pair correlations similar to biological MZ twin pairs and higher than biological DZ twin pairs. However, misclassified twin pairs show no difference in their within twin pair correlations to correctly classified twin pairs (Gunderson et al., 2006; Herle, Fildes, van Jaarsveld, Rijsdijk, & Llewellyn, 2016). This indicates that parent and family perceptions of zygosity do not cause violations of the equal environment assumption.

Another method to test this assumption is to measure environmental similarity within twin pairs. One study has tested environmental similarity using measures of childhood similarity, proportion of life living together, current contact, psychological intimacy and advice or support with co-twin (Felson, 2014). If the equal environments assumption is violated, then MZ twin pairs will have higher estimates on measures of environmental similarity. However, there was no evidence that environmental similarity differed across zygosity (Felson, 2014), suggesting that the equal environments assumption is valid.

Assumption 2: Genotype-environment effects are minimal

Though quantitative genetics aims to decompose trait variation into separate genetic and environmental influences, it is likely that the genetic and environmental factors acting upon a trait are not independent of each other (Plomin et al., 2013). There are three types of genotype-environment effects: genotype-environment correlation, genotype-environment interaction and assortative mating.

Many ‘environmental’ measures in the behavioural sciences show genetic influence (Plomin et al., 2013). A meta-analysis of 265 environmental variables estimated genetic influences accounted for 27% of the variation (Kendler & Baker, 2007). This indicates a genetic control of exposure to environments (Kendler & Eaves, 1986), referred to as *genotype-environment (GE) correlation* (Plomin et al., 2013). GE correlation occurs as the environment experienced by an individual is shaped by the individual or by their relatives, which can be active, passive or evocative (Jaffee & Price, 2007; Plomin et al., 2013). Positive gene-environment correlations will inflate twin heritability estimates and negative correlations will decrease heritability estimates (Rijsdijk & Sham, 2002).

Genotype-environment (GE) interaction is genetic sensitivity to environments (Plomin et al., 2013). This means that the effect of an environment on a trait is dependent on the genotype, and vice versa, the effect of a genotype on a trait is dependent upon the environment (Kendler & Eaves, 1986). GE interaction will always increase the variance in a trait because it must be zero (no difference in sensitivity) or positive (difference in sensitivity). It affects a trait independently of the effect of genetic and environmental influences alone. It is difficult to detect the effect of GE interaction on trait variation.

Adoption studies can detect GE interaction by measuring phenotypes in adoptees, their adoptive parents and their biological parents. If the child's phenotype differs depending on the adoptive and biological parents' phenotypes, then an interaction is present. For example, children with biological parents who had more psychopathology symptoms had fewer behavioural problems if the adoptive parents used more structured parenting compared to less structured parenting (Leve et al., 2009). Twin studies can also identify GE interaction by assessing whether heritability estimates of a trait change depending on the level of exposure of an environment (Tuvblad, Grann, & Lichtenstein, 2006).

Assortative mating, considered a type of GE interplay (Rutter, Moffitt, & Caspi, 2006), refers to any pairing within the population that is not random. Individuals that are more similar, either because of genetic or environmental reasons, may be more likely to pair as mates, which will increase genetic similarity between relatives (Rijsdijk & Sham, 2002). DZ twin pairs could therefore be more than 50% genetically similar, and estimates of the shared environment would be inflated. We can test for the presence of assortative mating by investigating the correlation between spouse pairs for a trait of interest. Research has found assortative mating has little effect on subjective wellbeing (Feng & Baker, 1994).

Quantitative methods assume that when gene-environment interplay is not controlled, it is having a minimal effect on the trait. However, there is evidence of gene-environment interplay for wellbeing (Wang, Davis, Wootton, Mottershaw, & Haworth, 2017; Wootton, Davis, Mottershaw, Wang, & Haworth, 2017). It is impossible to control for all environments that could be involved in GE interplay, and we should consider possible factors of GE interplay when interpreting the heritability and environment estimates for wellbeing.

Assumption 3: Genetic similarity for MZ twins is 100% and DZ twins is 50%

Heritability estimates from twin studies completely rely on the assumption that MZ twins are on average 100% similar genetically, and DZ twins are on average 50% similar genetically (that is, 50% similar for the DNA variants that vary between humans). However, there are instances where this assumption may be violated, such as de novo mutations that occur in the early stage embryo (Czyz & Ramagopalan, 2013).

Genetic similarity between twins is limited to DNA sequence variation, and everything else (including non-inherited epigenetic variation) is considered environmental (Plomin et al., 2013). MZ twins can differ in their DNA sequence due to changes to the DNA sequence that occur after the splitting of the embryo (Plomin et al., 2013). In addition, X chromosome inactivation occurs in females because only one X chromosome is expressed at any one time and which copy is inactivated can be non-random (Brown & Robinson, 2000). This can lead female MZ twin pairs to express X chromosomes differently from each other. These differences described rarely cause extreme discordance in MZ twins (Machin, 2009) and is unlikely to confound research using large twin samples.

The exact shared proportion of the DNA sequence inherited from each parent is on average 50% for DZ twins but can vary due to chance or assortative mating. Using genome-wide coverage of genetic markers, researchers have been able to measure the exact proportion of genetic similarity and use this to estimate heritability of behavioural traits. On average, the proportion of genetic similarity between sibling pairs was 0.498, and ranged 0.37 to 0.62

(Visscher et al., 2006). This shows that the assumption that on average, DZ twins are 50% similar genetically is reasonable.

Assumption 4: Twins are representative of singletons

There are genuine differences in pregnancy and childbirth of twins compared to singletons, including lower birth weight, more chance of pre-term births, and more complications (Machin, 2009). To overcome this, twin research uses strict exclusion criteria relating to complicated births, extremely low birth weight and premature births. Furthermore, approximately 75% of MZ twins are monochorionic (share one placenta, Vugt & Shulman, 2006) which further increases the dangers of twin pregnancy (Machin, 2009). It has been suggested that monochorionic twins are more similar than dichorionic twins, though few twin cohorts have collected data on chorion sharing to test this assumption. One large cohort study found little effect of chorion sharing for 66 psychological traits including subjective wellbeing (van Beijsterveldt et al., 2016).

Twins could be considered unrepresentative of the general population because they have another person with them across different life stages. Twins show slower language development compared to singletons (Rutter, Thorpe, Greenwood, Northstone, & Golding, 2003), which may be caused by parent-child interactions requiring constant shifts of attention instead of prolonged uninterrupted interactions observed with singletons (Rutter & Redshaw, 1991). However, this delay has disappeared by adolescence (Posthuma, De Geus, Bleichrodt, & Boomsma, 2000). Twins and non-twin siblings are comparable for intellectual ability (Posthuma et al., 2000), and twins are generalizable to singletons for physical health characteristics, including height, weight, and bone mineral density (Andrew et al., 2001) and personality characteristics (Johnson, Krueger, Bouchard, & McGue, 2002). Mean scores on wellbeing measures, such as the subjective happiness scale, are comparable to that of singletons (Wootton et al., 2017), and we therefore assume that twins are representative of the general population in terms of wellbeing.

2.1.3 Genetic and environmental sources of variance

As described above, individual differences in a trait can be decomposed into genetic and environmental influences (Rijsdijk & Sham, 2002). The genetic influences, known as heritability, explain substantial proportions of variance. A meta-analysis of almost 18,000 human traits reported an average heritability estimate of 49% (Polderman et al., 2015). Environmental influences explain the remainder of the variance which is not explained by genetic influences.

2.1.3.1 Heritability

Heritability is a statistical parameter (often represented by h^2) that refers to the proportion of population variance in a trait that can be accounted for by genetic differences between individuals (Plomin et al., 2013). Heritability can be categorised as narrow sense heritability or broad sense heritability. Narrow sense heritability is the proportion of the variance accounted for by additive genetic influences that accumulatively contribute to trait variance. Broad sense heritability is additive and non-additive genetic influences, such as gene interaction and dominance effects. In this thesis, heritability is used to refer to narrow sense heritability, unless otherwise stated. Estimating heritability using the twin design is discussed in detail in Chapter 3.

Heritability is dynamic and can change across time and population (Haworth & Davis, 2014). Twin heritability estimates generally increase with age (Haworth et al., 2008, 2010; Bergen, Gardner, & Kendler, 2007), which has been supported by evidence from DNA-based statistical methods (Trzaskowski, Yang, Visscher, & Plomin, 2014). However, some traits show a decrease in heritability estimates across age, such as personality, and different traits reach stable heritability estimates at different ages (Briley & Tucker-Drob, 2017). This emphasises the importance of considering the age of participants when interpreting heritability estimates.

2.1.3.2 Environmental influences

In behavioural genetics, an environmental influence is anything that explains a proportion of the variation in an observed trait beyond genetic factors (Plomin et al., 2013). Any nongenetic influence that increases similarity between family members is known as shared (or sometimes common) environmental influences. Any nongenetic influence that causes dissimilarity between family members is known as nonshared environmental influences (NSE).

2.1.3.2.1 Shared environmental influences

Shared environmental influences often account for a small proportion of the variance in behavioural traits, much less than expected when human behavioural genetics first began (Plomin & Daniels, 1987). A meta-analysis of many human traits estimated that 17% of the variance could be explained by shared environments (Polderman et al., 2015) and studies of mental health and wellbeing consistently show that shared environments account for the smallest proportion of trait variation (Bartels et al., 2004; Burt, 2009; Bartels, 2015).

It has been suggested that the often-found nonsignificant estimate of shared environments is due to a lack of power (Burt, 2009), which is likely true for earlier studies with small sample sizes. However, one study found that the shared environment did not explain any of the variation in depressive symptoms in adults over 40 years with a sample of approximately 25,000 twins obtained by pooling many twin cohorts (Petkus et al., 2017). Using a power calculator developed for twin modelling (Verhulst, 2017), I calculated that this study had 80% power to detect estimates of 5% shared environmental influence, but only 50% power to detect an estimate of 1% shared environmental influence. This suggests the shared environment only explains a small proportion of the variation in depression in adults and indicates that lack of power may not explain why we do not find large shared environment contributions.

The small effects of shared environmental influences do not mean that families (beyond genetic influences) are not important. It is possible that shared family environments effect individuals specifically rather than on a family level (Plomin et al., 2016). Individuals can interpret even the same environment slightly differently, which could be captured as part of the nonshared environmental influences instead.

2.1.3.2.2 Nonshared environmental influences (NSE)

Nonshared environmental influences (NSE) are nongenetic influences that are independent (uncorrelated) between family members, including measurement error (Plomin et al., 2013). Generally, NSE explains a substantial amount of the variation in human traits (34% in the meta-analysis of twin studies, Polderman et al., 2015) and is a major source of variation in behavioural traits (Plomin & Daniels, 2011). Nonshared environmental influences could occur within the family environment, such as different parental treatment, or environments outside the family, such as different peer groups. It could also be due to different perceptions of the same environment, such as family income, where family income influences the experience of each sibling instead of affecting both siblings identically. This is an important finding from twin studies because it suggests that phenotypic analyses should consider the effects of family-wide factors, such as socio-economic status and number of children, on individual members of the family.

The importance of NSE influences was first outlined three decades ago with three steps for future research: to identify experiences that are not shared by siblings; to relate these NSE experiences to differences in sibling behaviour; and to address causality (Plomin & Daniels, 1987). Research has identified specific environmental influences using identical twins to control for genetics and shared environments, and measures of systematic environmental differences such as birthweight, perception of the classroom environment, and friendship quality (Asbury, Dunn, & Plomin, 2006; Asbury & Plomin, 2017; Oliver, Pike, & Plomin, 2008). Specific NSE have little effect individually, but together account for a substantial proportion of the variation in behavioural traits, in a similar way to the effect of genetic variants on complex traits (Plomin et al., 2016).

It is important to consider the effect of unsystematic NSE, such as accidents, chance and other life events (Davey Smith, 2011). These are difficult to measure but likely account for a substantial proportion of NSE. NSE influences cannot be distinguished from measurement error in standard twin studies and is a significant limitation of the design. Measurement error will inflate NSE and decrease heritability estimates.

2.2 Heritability and environmental influences on wellbeing

In 2015, a meta-analysis identified 30 twin-family studies that together provided 70 heritability estimates of wellbeing, which ranged from 0 to 64% (Bartels, 2015). Estimates of the shared environment were generally not reported because the shared environment did not account for any variation in wellbeing. Across the 15 studies that reported estimates of shared environmental influences, the average was 7%. In contrast, nonshared environmental influences were generally above 50% (range 31 to 100%). However, with these large ranges it is difficult to draw firm conclusions about the proportion of variation in wellbeing accounted for by genetic and environmental influences.

To provide more robust heritability estimates, 12 heritability estimates from 10 studies of overall wellbeing and 10 heritability estimates from 9 studies of life satisfaction were meta-analysed (Bartels, 2015). Only including independent samples, the weighted average heritability estimate for overall wellbeing was 36% (range 23 to 59%) and for life satisfaction was 32% (18 to 47%). Though lower than the 49% average heritability of human traits (Polderman et al., 2015), these estimates are comparable with meta-analyses of internalising symptoms, which report heritability estimates of 37% for depression (Sullivan et al., 2000) and 32% for anxiety (Hettema, Neale, & Kendler, 2001). These findings indicate that genetic influences explain a substantial proportion of the variation in wellbeing, but environmental influences explain much more. In the meta-analysis of wellbeing, overall wellbeing included measures of subjective wellbeing, psychological wellbeing, emotional wellbeing, social wellbeing, life satisfaction and happiness. Life satisfaction ranged from single item measures to wider measures of satisfaction. Therefore, these heritability estimates are moderate considering the heterogeneity in the measures.

As heritability (and therefore environmental) estimates can vary across age (Bergen, Gardner, & Kendler, 2007), it is important to consider the heritability estimates of wellbeing from samples of adolescents and young people. To provide a review of the publications that have investigated the genetic and environmental influences on wellbeing in adolescence, I performed a literature search using Scopus (www.scopus.com) and the key words *life satisfaction, happiness* or *wellbeing* and *twin* and *adolescence* or *adolescent* or *young* within the title, abstract or keywords. This resulted in 81 documents, and after a review of the abstracts, 24 publications appeared relevant. After reading the papers from the search and from Bartels (2015), 12 publications were relevant. These are summarised in Appendix 2.1. The 12 studies are from four countries in western Europe, reporting on five samples aged between 12 and 20 years. Together, these studies capture wellbeing through adolescence.

Eleven of the studies measure at least one component of subjective wellbeing (affect or happiness or life satisfaction), but only four studies measure at least one eudaimonic trait. This suggests further research should explore the heritability and environmental influences on wellbeing in adolescence using both subjective and eudaimonic wellbeing indicators. Furthermore, the studies that measure both subjective and eudaimonic wellbeing combined a variety of positive traits as indicators of wellbeing, such as optimism (Fagnani et al., 2017; Wang et al., 2017; Wootton et al., 2017) self-esteem (Fagnani et al., 2017) and hope (Wang et al., 2017; Wootton et al., 2017). It is not clear why traits such as self-esteem are considered indicators of wellbeing. As discussed in Chapter 1, this again emphasises the lack of consistency in the measurement of wellbeing across the literature.

2.2.1 Heritability of wellbeing in adolescence

To calculate the average heritability estimate across the studies in my literature review, I followed the same analysis process as Bartels (2015). I define wellbeing as an overarching construct for subjective wellbeing and eudaimonic wellbeing indicators. Consequently, I calculated heritability estimates for subjective wellbeing and eudaimonic wellbeing separately. The components of subjective wellbeing were measured frequently: nine studies specifically use measures of life satisfaction and eleven studies specifically measure happiness as a component of subjective wellbeing using the subjective happiness scale (Lyubomirsky & Lepper, 1999). Consequently, I also calculated separate heritability estimates for happiness and life satisfaction. As many studies had overlapping samples, I selected independent samples from studies with the largest sample size and the reporting of sex specific estimates. Where studies reported sex specific estimates, I treated each estimate as being from independent samples. Where studies reported estimates for more than one wellbeing indicator, I took an average estimate.

The weighted average heritability estimate for subjective wellbeing in adolescence and young adulthood (age range: 12 to 20 years), based on three estimates from two studies (Bartels, Cacioppo, van Beijsterveldt, & Boomsma, 2013; Haworth, Carter, Eley, & Plomin, 2015) was 40% and the estimate for eudaimonic wellbeing was 42% based on two estimates (Fagnani et al., 2017; Wootton et al., 2017). Both estimates are larger than the heritability estimate of 36% from the previous meta-analysis, which included samples with a mean age ranging 16 to 65 years, and with an average age across the samples of 37 years (Bartels, 2015). This may suggest that wellbeing is more heritable during adolescence compared to later life.

The weighted average estimate for life satisfaction based on two estimates (Bartels & Boomsma, 2009; Haworth et al., 2015) was 45%, which again is much higher than the 32% reported in Bartels (2015). The weighted average estimate for subjective happiness was 34% based on four estimates from three independent studies (Bartels et al., 2010; Fagnani et al., 2017; Haworth et al., 2015). These results indicate that life satisfaction may be more heritable than subjective happiness during adolescence.

2.2.2 Environmental influences on wellbeing in adolescence

The studies in my literature review of adolescent wellbeing also provide estimates of the shared and nonshared environmental influences on wellbeing in adolescence and emerging adulthood. Most studies have used statistical designs that only estimate the genetic and nonshared environmental influences as the shared environment appears to have little influence on wellbeing. Of the publications that model shared environmental influences, the estimates range from 0 to 17%, though most estimates are 0%, supporting the findings from Bartels (2015).

As with the heritability estimates, I calculated weighted average estimates of the nonshared environmental influences for subjective wellbeing, eudaimonic wellbeing and the specific components of subjective wellbeing. Using independent samples, the weighted average estimates of the proportion of variation explained by nonshared environmental influences were 48% for subjective wellbeing (based on seven estimates from five independent studies), 57% for eudaimonic wellbeing (based on two estimates), 61% for subjective happiness (based on four estimates from three studies), and 42% for life satisfaction (based on five estimates). These findings indicate that nonshared environmental influences are more important for eudaimonic wellbeing than for subjective wellbeing, though with only two studies of eudaimonic wellbeing it is difficult to draw conclusions. Nonshared environmental influences also account for more variation in subjective happiness than life satisfaction, emphasising the specificity in subjective wellbeing components and highlighting the need for research that explores the aetiology of individual wellbeing components. Generally, these findings suggest that nonshared environmental influences are just as important as genetic influence in explaining variation in wellbeing in adolescence. Research is needed to uncover the specific environmental experiences that are causing this variation, which is addressed in Chapter 6.

2.2.3 Genetic and environmental overlap between wellbeing indicators

Multivariate analysis allows us to go beyond decomposing the variance of a single trait to estimate the relative contributions of genetic and environmental influences to the covariance between traits (Plomin et al., 2013). We can apply this to wellbeing to understand whether the same genetic and environmental factors affect the components of subjective and eudaimonic wellbeing. Few studies have investigated wellbeing using multivariate analysis and measures of subjective wellbeing or eudaimonic wellbeing. Consequently, I discuss literature that uses both adult and adolescent samples.

2.2.3.1 Genetic overlap between subjective wellbeing indicators

Two studies have explored the genetic overlap between components of subjective wellbeing in adolescence using twin designs. Both studies provide estimates of the proportion of the phenotypic correlation between life satisfaction and happiness that is accounted for by genetic influences, a statistic known as bivariate heritability (Haworth et al., 2015). Both studies report similar estimates: 0.50 (Haworth et al., 2015) and 0.51 (Bartels & Boomsma, 2009), which indicates that approximately 50% of the phenotypic correlation (which is 0.61 in Haworth et al., 2015, and 0.77 in Bartels & Boomsma, 2009) between happiness and life satisfaction is attributable to genetic influences. This is higher than the 0.37 bivariate heritability estimate between depression and emotional symptoms, where the phenotypic correlation was 0.64 (Haworth et al., 2015). These results indicate that genetic and environmental influences are equally important to the strong phenotypic relationship between the components of subjective wellbeing.

2.2.3.2 Genetic overlap between eudaimonic wellbeing indicators

Five studies estimate the genetic overlap between eudaimonic wellbeing indicators by calculating the genetic correlations between the different indicators. The genetic correlation provides an estimate of the extent that the genetic influences that affect one trait correlate with the genetic influences that affect a second trait, independent of the heritability estimates of the traits (Plomin et al., 2013).

Two studies have used Ryff's (1989) six scales of psychological wellbeing and find substantial genetic overlap, though the magnitude of overlap varies greatly. In a sample of adults, the genetic correlations ranged from 0.27 (autonomy and purpose in life) to 0.98 (self-acceptance and environmental mastery) (Archontaki et al., 2013). More consistent genetic correlations were found using a sample of adolescents, ranging from 0.70 (autonomy and personal growth) to 0.99 (self-acceptance and positive relations) (Gigantesco et al., 2011). These differences may be due to age, but could be due to other confounders including differences in measurement (the 18-item measure in Gigantesco et al., 2011, compared to the 42-item in Archontaki et al., 2013) or sample location (Italy, Gigantesco et al. 2011, compared to the US, Archontaki, 2013). The genetic correlations between purpose in life and the other components was consistently lower for the adult sample (Archontaki et al., 2013), which could perhaps reflect the response behaviour of adolescents. It may be difficult for adolescents to respond to more eudaimonic items such as purpose in life due to their limited experience and ability to give their lives purpose.

A further three studies report genetic correlations between more diverse eudaimonic wellbeing indicators (Caprara et al., 2009; Franz et al., 2012; Gatt, Burton, Schofield, Bryant, & Williams, 2014). Across these studies, the genetic correlations ranged 0.30 to 0.95, again indicating much variation in the genetic overlap between eudaimonic traits. The weakest genetic correlation was between two components of the COMPAS-W (composure during stress and achievement and goal orientation, Gatt et al., 2014) and the strongest genetic correlation was reported between self-esteem and a composite of Ryff's six scales of psychological wellbeing (Franz et al., 2012). Two studies reported all their genetic correlations between eudaimonic traits above 0.69 (Caprara et al., 2009; Franz et al., 2012), which suggests there is substantial genetic overlap between eudaimonic indicators. However, the studies reported here use components of different scales (e.g. Gatt et al., 2014), create composites from different scales (Franz et al., 2012), or use traits not traditionally considered as components of wellbeing (Caprara et al., 2009; Franz et al., 2012). Future research needs to explore the genetic overlap between diverse eudaimonic wellbeing indicators using validated instruments. This is addressed in Chapter 5.

2.2.3.3 Genetic overlap between subjective and eudaimonic wellbeing indicators

A recent molecular genetic study of subjective wellbeing (measured as happiness) and eudaimonic wellbeing (measured as meaning in life) reported a genetic correlation of 0.78 (Baselmans & Bartels, 2018), suggesting the common genetic variants on subjective and eudaimonic wellbeing largely overlap. Estimates of the genetic correlations between subjective and eudaimonic wellbeing from quantitative genetic studies support this high genetic correlation, where the average estimate across studies reporting the genetic correlation between life satisfaction and a range of eudaimonic traits ranges 0.64 to 0.84 (Caprara et al., 2009; Franz et al., 2012; Gatt et al., 2014). These studies indicate that the genetic factors that influence subjective wellbeing largely also influence eudaimonic wellbeing indicators.

Additionally, one study has explored the shared heritability between psychological (or eudaimonic), social and emotional (or subjective) wellbeing by assessing each component's relationship with one overall latent factor of wellbeing (Keyes, Myers, & Kendler, 2010). The genetic effects on each component were mainly shared with the genetic influences on the overarching wellbeing factor, with 61% of the genetic effects on social wellbeing, 65% on emotional wellbeing and 99% on psychological wellbeing. This indicates that psychological (eudaimonic) wellbeing was the best indicator of the propensity of overall wellbeing (Keyes et al., 2010), and emphasises the importance of using more diverse indicators of wellbeing that go beyond the components of subjective wellbeing.

Overall, these findings indicate a large genetic overlap between subjective and eudaimonic wellbeing. However, it is difficult to assess the differences because there is no consistency in the measures used as indicators of eudaimonic wellbeing, ranging from composure during stress (Gatt et al., 2014) to self-esteem (Caprara et al., 2009; Franz et al., 2012). Often researchers have created composites of subjective and eudaimonic wellbeing rather than using individual dimensions from original scales. For example, Ryff's scales of psychological wellbeing was not developed as a single measure of eudaimonic wellbeing yet is used as a composite in two studies (Franz et al., 2012; Keyes et al., 2010). More research is needed that explores the shared genetic influence across diverse wellbeing indicators in adolescence, without using composites of subjective and eudaimonic wellbeing. This will be addressed in Chapter 5.

In summary, there is some specificity in the magnitude of the heritability estimates across the subjective wellbeing components, though we need more research to draw conclusions on the specificity of eudaimonic wellbeing indicators. We observe a large genetic overlap between components of subjective wellbeing and different eudaimonic wellbeing indicators, but we need further research using validated scales to measure eudaimonic wellbeing to understand the genetic overlap between subjective wellbeing and diverse eudaimonic wellbeing indicators.

2.2.3.4 Nonshared environmental overlap between subjective wellbeing indicators

Two studies provide estimates of the proportion of the phenotypic correlation between life satisfaction and happiness that is accounted for by nonshared environmental influences. One study decomposed the variance into genetic and nonshared environmental influences, excluding the shared environment because it explained no variance in the traits (Bartels & Boomsma, 2009). Consequently, the estimate of the proportion of the phenotypic correlation (r = 0.77) accounted for by nonshared environmental influences was 49%, which is the remainder after the bivariate heritability has been accounted for. The second study found shared environmental influences on the traits, and therefore modelled genetic, shared environmental and nonshared environmental influences, reporting that nonshared environmental influences explained 38% of the phenotypic correlation (r = 0.61) between happiness and life satisfaction (Haworth et al., 2015). Though there is substantial overlap between the nonshared environmental influences on the components of wellbeing, it is possible they are smaller than the overlap between genetic influences. However, more research is needed to draw strong conclusions.

2.2.3.5 Nonshared environmental overlap between eudaimonic wellbeing indicators

Across the studies that explore nonshared environmental overlap between eudaimonic wellbeing indicators, most report nonshared environmental correlations lower than 0.50 (Archontaki et al., 2013; Gatt et al., 2014; Franz et al. 2012; Caprara et al., 2009). This suggests that nonshared environmental influences are largely unique to each component of eudaimonic wellbeing. This may indicate that a wide variety of environmental experiences are needed to experience eudaimonic wellbeing.

However, two studies report nonshared environmental correlations above 0.50. One study reports a nonshared correlation of 0.58 between own-worth and environmental mastery (Gatt et al., 2014), which suggests the nonshared environmental influences on these eudaimonic wellbeing indicators are more similar than other eudaimonic indicators. These traits are also arguably more similar than other eudaimonic traits, and it is possible that self-worth is needed to achieve self-perceived control over your environment. Consequently, it is plausible that largely the same environmental factors influence both traits. Furthermore, nine of the 15 nonshared environmental correlations between Ryff's six scales of psychological wellbeing were above 0.50 for a sample of adolescents (Gigantesco et al., 2011). This could suggest that during adolescence, the environments that influence different eudaimonic wellbeing indicators largely overlap. However, the range in the nonshared environmental correlations was large: from 0.01 (autonomy and personal growth) to 0.89 (environmental mastery and self-acceptance), which may be due to the small sample size (only 284 complete twin pairs).

2.2.3.6 Nonshared environmental overlap between subjective and eudaimonic wellbeing indicators

Three studies together provide estimates of the nonshared environmental overlap between subjective wellbeing and eudaimonic wellbeing by reporting nonshared environmental correlations between life satisfaction and nine diverse eudaimonic traits (Caprara et al., 2009; Franz et al., 2012; Gatt et al., 2014). Across the studies, only three correlations were greater than 0.50, suggesting low nonshared environmental overlap between subjective and eudaimonic wellbeing. Using the COMPAS-W (Gatt et al., 2014), the nonshared environmental correlation between life satisfaction and self-worth was 0.56, composure was 0.57, and positivity was 0.59. The nonshared environmental correlations between life satisfaction and mastery and achievement were less than 0.30 and not reported (Gatt et al., 2014). The lowest nonshared environmental correlation reported was 0.18 between life satisfaction and self-esteem (Caprara et al., 2009), indicating there are few nonshared environmental influences that overlap between self-esteem and life satisfaction. This again raises the issue of the positive traits that constitute eudaimonic wellbeing. It is possible that self-esteem is not a component of wellbeing and instead is better conceptualised as a correlate of wellbeing.

In summary, it appears that although some nonshared environmental influences are shared across different wellbeing indicators, there are also nonshared environmental influences unique to each aspect of wellbeing. There is greater overlap in the genetic influences than environmental influences on wellbeing. There is also greater specificity in the nonshared environmental overlap between different components of wellbeing, though we need more research that uses validated measures of eudaimonic wellbeing to draw strong conclusions. Future research should focus on identifying specific environments that influence subjective and eudaimonic wellbeing in different ways. This is investigated in Chapters 6 and 7 of this thesis.

2.3 Specific Environmental influences on wellbeing

The traditional twin design decomposes the variance of a trait into genetic and environmental influence, providing estimates of the overall contribution of these influences but no information into what these specific influences are. Much molecular genetic research has explored the contribution of common genetic variants to wellbeing (Baselmans &

Bartels, 2018; Okbay et al., 2016), yet research aimed to identify specific environmental influences on wellbeing has received less attention. We need more research that measures specific environments and explores how these are associated with the components of wellbeing. Ideally, this should use a genetically informative design to control for the influence of genetic confounders. This design will be explained in more detail in Chapter 6.

By identifying environmental influences on wellbeing, we can inform possible interventions. For example, bullying is a nonshared environmental influence on social anxiety, and contributes to poor mental health in children and adolescents (Silberg et al., 2016), which suggests mental health should be assessed in victims of bullying. Furthermore, finding that access to green space is a nonshared environmental influence on depression but not anxiety or stress (Cohen-Cline, Turkheimer, & Duncan, 2015) suggests improving access to green space is a plausible intervention for depression, but not for anxiety or stress.

Given the length of time that adolescents spend at school, it would be logical to consider the school environment as a candidate for an environmental influence on wellbeing. School experiences in young schoolchildren have been associated with later mental health problems in an epidemiological study (Waenerlund et al., 2016). A systematic review found some evidence that school level effects including teacher support and school connectedness are associated with better emotional health (Kidger, Araya, Donovan, & Gunnell, 2012), but there was also evidence that student level differences, such as level of depression, explained more variance than school effects (Roeger, Allison, Martin, Dadds, & Keeves, 2001). This suggests a need for further research that can identify whether the school environment is a specific nonshared environmental influence on mental health and wellbeing.

Twin studies have indicated the existence of genotype-environment correlations (as defined above) whereby wellbeing is genetically associated with aspects of the environment including social relationships (Wang et al., 2017), family conflict (Van der Aa, Boomsma, Rebollo-Mesa, Hudziak, & Bartels, 2010), and life events (Wootton et al., 2017). This means that traditionally considered environmental measures are genetically mediated, and there is genetic overlap between these environmental measures and wellbeing. Twin studies have also indicated the presence of genotype-environment interaction, with changes in heritability estimates of wellbeing due to different conditions in the environment, including parental divorce (Van der Aa et al., 2010), marital status (Nes, Czajkowski, & Tambs, 2010), and financial situations (Johnson & Krueger, 2006). This suggests that the environmental context in which individuals live causes variation in wellbeing. Further exploration of the specific environmental influences on wellbeing beyond observational studies is essential. This will be addressed in Chapter 6, where I explore specific environmental influences on wellbeing whilst controlling for genetic influences.

2.4 Chapter Summary

Behavioural genetics refers to the scientific study of genetic and environmental influences on behaviours and disorders, and twin studies are one quantitative method used to achieve this. Twin studies allow us to decompose the population variation of a trait into genetic influences, shared environmental influences, and nonshared environmental influences.

Though assumptions are made in twin studies, evidence suggests they are acceptable for studies of wellbeing.

Current knowledge from studies of wellbeing using twin studies suggest that heritability and nonshared environmental influences explain substantial proportions of the variation in wellbeing, whereas shared environmental influences have little effect. Heritability estimates from a meta-analysis were 36% for overall wellbeing (Bartels, 2015), and mean heritability estimates for wellbeing in adolescence and emerging adulthood are 46%. Environmental influences on wellbeing are generally above 50%, suggesting that nonshared environmental influences explain more of the variation in wellbeing than genetic factors. Though both subjective and eudaimonic wellbeing measures have been used to explore the variability in wellbeing in adolescence, few studies use validated scales to capture eudaimonic wellbeing, and there is no consistency in the psychological characteristics used to represent eudaimonic wellbeing. Estimates of the genetic and environmental overlap between components of wellbeing show that genetic influences are largely similar, and nonshared environmental factors overlap to a lesser extent. There may be some differences in the causes of variation across subjective and eudaimonic measures of wellbeing, but this may be due to differences in the measurement of eudaimonic wellbeing. More research is needed to identify the genetic and environmental similarity between diverse wellbeing indicators in adolescence, and to identify specific nonshared environmental influences on wellbeing.

In the next chapter, I will outline the sample, measures and methods used in this thesis.

Chapter 3. Sample, measures and statistical procedures

This chapter will first describe the sample used in this thesis, and second describe the main statistical procedures I have used. I provide detailed information about the demographics and measures used from the Twins Early Development Study (TEDS), the sample I have used in every empirical chapter. I then discuss the twin design and how it has been applied to the wellbeing indicators, and Principal Components Analysis, which has been used in two of the empirical chapters. More specific methods are discussed within each empirical chapter.

3.1 Twins Early Development Study (TEDS)

3.1.1 Sample overview

The Twins Early Development Study (TEDS) is a longitudinal cohort study of twins born in England and Wales between 1994 and 1996. 16,810 families were identified as eligible to take part based on the ONS data records of live twin births in England and Wales, and were contacted by the ONS and asked whether they would like to take part in TEDS. 16,302 families were contacted by TEDS, 97% of eligible families. 508 families were not contacted because they withdrew or there were address problems. At first contact, 13,488 (82.7%) of the families contacted provided data. Zygosity was assessed through parental questionnaires of physical similarity, which was over 95% accurate compared to DNA testing (Price et al., 2000), and where zygosity was unclear, DNA testing was conducted. The TEDS sample was representative of the general UK population at first contact (Haworth, Davis, & Plomin, 2013), and has remained representative despite attrition (Kovas et al., 2007).

Exclusion criteria included medical exclusions, any perinatal outliers, unknown sex or zygosity, and absence of data from first contact. Exclusion criteria were applied to the dataset on a pair-wise basis; if either twin met the exclusion criteria, both twins' data were removed. The medical exclusions were applied to the family if either or both twins suffered from at least one of the following nine conditions: autism/ASD; cerebral palsy; any genetic, chromosomal or inherited disorder; brain damage or disorders affecting brain function; Downs syndrome; profound deafness; global development delay; complete blindness; death of either twin. Families were considered as perinatal outliers if either twin or the mother was subject to extreme adverse circumstances at or around the time of birth, reported at first contact. The five perinatal conditions were: low birth weight (< 471g); short gestational age (< 27 weeks); maternal drinking during pregnancy (≥ 14 units per week); long period of special care after birth (> 97 days); long stay in hospital after birth (> 74 days).

TEDS has mainly focused on collecting cognitive and behavioural data, as well as difficulties in normal development (Haworth et al., 2013). Assessments have included: cognitive, learning, and reading ability; parenting; child behavioural problems; health; school and home environments. Child behavioural problems have included mental health, such as anxiety and depression, conduct problems, and developmental disorders including autistic spectrum and attention-deficit hyperactivity disorder (ADHD). Cognitive ability was also tested using web-based assessments, and exam results were collected at age 16 when participants had completed exams for the General Certificate of Secondary Education (GCSEs) which are compulsory end-of-school assessments in the UK. Across the two decades of data collection, TEDS have collected data from parents, children and teachers. Data collection has relied more closely on the twins as they have aged.

3.1.1.1 Data collection of wellbeing at age 16

When the twins were 16 years old, 10,874 TEDS families (64.7% of the families originally eligible) were invited to participate in data collection. The twins provided informed consent after parental consent was gained. Data were collected online and by post using self-report measures. Online data collection included topics of family, home, school and classroom environments, and relationships. Booklet data collection (collected via postal questionnaires) included measures of self-reported behaviour, schizotypy and wellbeing. Due to funding, the online data collection was only open to twins born between January 1994 and August 1995, and 6,281 families were contacted of the original 9,410 eligible families. For the first cohort (born January 1994 to August 1994), the web study took place in September 2010. For the second cohort (born September 1994 to August 1995), the web study took place in June 2011. The booklet measure (collected via postal questionnaires) was open to all families in TEDS, and all 10,874 active TEDS families were contacted. The first wave of the booklet took place in February 2011 for the first cohort (born January 1994 to August 1994) and the second wave for all other TEDS cohorts took place in December 2011. Consequently, the booklet collection was approximately 6 months after the online study. The response rate for online collection was 50.6% (at least one twin had partial or complete web data) and the booklet was 47.3% (at least one twin had returned a booklet). The sample remained representative of the whole TEDS sample in terms of ethnicity, sex and zygosity (Haworth et al., 2013).

We excluded 962 individuals (481 families) based on the exclusion criteria outlined above (246 families were excluded due to medical exclusions; 130 were perinatal outliers; 98

unknown sex or zygosity; 6 other reasons). Participants were required to have completed at least 50% of one wellbeing measure to be included in the wellbeing analysis. This resulted in a sample of 10,927 individuals (55.43% female; 36.12% MZ), including 5,302 complete twin pairs (1,931 monozygotic and 3,371 dizygotic pairs). 9,645 individuals provided at least one booklet measure, and 5,340 individuals provided at least one web measure. 2,161 individuals had complete data for every wellbeing measure across web and booklet data collection. The mean age at assessment was 16.67 years (SD = 0.33; range = 15.82 – 18.76) across both forms of data collection. The mean age for the web study was 16.48 (SD = 0.27) years and 16.86 (SD = 0.28) years for the booklet study.

3.1.2 Wellbeing measures

The wellbeing measures in TEDS (see Appendix 3.1 for a copy of the scales) were selected for inclusion based on a review of available scales appropriate for an adolescent age group. The final measures were decided upon following discussion with the TEDS team of administrators and researchers and based on feedback and psychometric performance during the pilot study. In a few instances, due to space constraints, we were unable to include all the original items from these scales. A total of 2 scales relating to subjective wellbeing and 13 scales relating to eudaimonic wellbeing were collected, resulting in an internationally unique dataset on adolescent wellbeing. In this thesis, I compare only 14 of the 15 measures because one measure (mindfulness) was collected in a separate wave of data collection using only a subsample of the TEDS twins.

Of the 15 wellbeing measures collected in TEDS, nine were collected online (life satisfaction, subjective happiness, optimism, gratitude, hopefulness, grit, ambition, curiosity, and subjective health), and eight were collected using the booklet (life satisfaction, subjective happiness, the basic psychological needs (autonomy, competence, relatedness), meaning in life, trust, and mindfulness). Life satisfaction and subjective happiness measures were used to represent subjective wellbeing, and all the other measures were considered eudaimonic wellbeing indicators. Life satisfaction and subjective happiness measures were included in web and booklet data collection, and for some analyses in this thesis where individuals had data for both collection methods, a mean score was calculated. Table 3.1 provides a description of the web and booklet measures. We created composites for all measures of wellbeing, which required at least 50% of the items to be non-missing.

Table 3.1 Description of wellbeing measures, split by data collection method.

Construct	Measure	Reference	Number of items (reversed)	Example item	Response scale
Web measures					
Life satisfaction	Multidimensional Student's Life Satisfaction Scale[a]	Huebner (1994)	21 (5)	I like being in school	six-points: 'strongly agree' to 'strongly disagree'
Subjective happiness	Subjective Happiness Scale	Lyubomirsky & Lepper (1999)	4 (1)	In general I consider myself: (response: not a very happy person/a very happy person)	seven-points, with different descriptions e.g. 'not a very happy person' to 'a very happy person'
Hopefulness	Children's Hope Scale	Snyder et al. (1997)	6	I think I am doing pretty well	six-points: 'all of the time' to 'none of the time'
Gratitude	Gratitude Questionnaire-6	McCullough, Emmons, & Tsang (2002)	6 (2)	I have so much in life to be thankful for	seven-points: 'strongly agree' to 'strongly disagree'
Optimism	Life Orientation Test – Revised	Scheier, Carver, & Bridges (1994)	6 (2)	I'm always optimistic about my future	five-points: 'very much like me' to 'not like me at all'
Ambition	Ambition Scale	Duckworth, Peterson, Matthews, & Kelly (2007)	5 (1)	I am driven to succeed	five-points: 'very much like me' to 'not like me at all'
Grit	Short Grit Scale	Duckworth & Quinn (2009)	8 (4)	I finish whatever I begin	five-points: 'very much like me' to 'not like me at all'
Curiosity	Curiosity And Exploration Inventory	Kashdan, Rose, & Fincham (2004)	7 (1)	Everywhere I go, I am looking out for new things or experiences	seven-points: 'strongly agree' to 'strongly disagree'
Health	Single Item From KIDSCREEN-52	Ravens-Sieberer et al. (2008)	1	In general, how would you say your health is?	five-points: 'excellent' to 'poor'

Construct	Measure	Reference	Number of items (reversed)	Example item	Response scale
Booklet measures					
Life satisfaction	Brief Multidimensional Student Life Satisfaction Scale	Seligson, Huebner, & Valois (2003)	6	How happy are you with your friendships?	seven-points: ‘very dissatisfied’ to ‘very satisfied’
Subjective happiness	Subjective Happiness Scale	Lyubomirsky & Lepper (1999)	4 (1)	In general I consider myself: (response: not a very happy person/a very happy person)	seven-points, with different descriptions e.g. ‘not a very happy person’ to ‘a very happy person’
Relatedness	Basic Psychological Needs Satisfaction Scale	Deci & Ryan (2000)	8 (3)	People in my life care about me	seven-points: ‘not very true at all’ to ‘very true’
Autonomy	Basic Psychological Needs Satisfaction Scale	Deci & Ryan (2000)	7 (3)	I generally feel free to express my ideas and opinions	seven-points: ‘not very true at all’ to ‘very true’
Competence	Basic Psychological Needs Satisfaction Scale	Deci & Ryan (2000)	6 (3)	I have been able to learn interesting new skills recently	seven-points: ‘not very true at all’ to ‘very true’
Meaning in life	Meaningful Life Measure[b]	Morgan & Farsides (2009)	5	My life is significant	seven-points: ‘strongly disagree’ to ‘strongly agree’
Trust	Social Trust	Gallup World Poll (2006)	1	In general, I think people can be trusted	‘yes’ or ‘no’
Mindfulness	Mindful Attention Awareness Scale[c]	Van Dam, Earleywine & Borders (2010)	5 (5)	I rush through activities without really being attentive to them	Six-points: ‘almost never’ to ‘almost always’

[a] Reduced due to space constraints from 40 items to 21 after an initial pilot study.

[b] Due to space constraints, one item was selected from each of the five original subscales (purposeful, valued, accomplished, principled and exciting life).

[c] Due to space constraints, 10 of the 15 scale items were removed after an initial pilot study.

3.1.3 Descriptive statistics of wellbeing measures

The descriptive statistics are reported in Table 3.2. We expected the underlying distribution of the measures to be skewed towards better wellbeing, however only life satisfaction and trust from the booklet dataset exceed the ±1 cut-off for acceptable skew (Tabachnick, Fidell, & others, 2001). All measures were transformed using van der Waerden transformation. The transformed and untransformed distributions are in Appendix 3.2. Analyses were conducted on the van der Waerden transformed and untransformed measures, however there was no difference to the results. Consequently, the analyses presented in the chapters of this thesis are conducted on the untransformed measures.

The means for the wellbeing scales reported in Table 3.2 are similar to the means previously reported for young samples (Duckworth & Quinn, 2009; Huebner, 1994; Kashdan et al., 2004; Lyubomirsky & Lepper, 1999; McCullough et al., 2002; Scheier et al., 1994; Seligson et al., 2003; Snyder et al., 1997). I calculated eta squared effect sizes to assess the percentage of variance explained in each wellbeing indicator by sex and by zygosity. For zygosity, there were significant differences for curiosity and grit, where DZ twins have higher means for curiosity and MZ twins are higher for grit. However, the effect was small and zygosity explained 0.003% of the variance in curiosity and 0.002% in grit, so I concluded the effect of zygosity was not meaningful. Effect sizes were also small (all less than 0.015%) for sex differences, but there were significant differences on 12 of the 14 measures. Females had lower means on nine measures, which represent both subjective and eudaimonic wellbeing (life satisfaction, optimism, trust, meaning in life, hopefulness, ambition, curiosity, grit and health). This suggests that females may have generally lower wellbeing in adolescence and follows similar patters to previous reports of lower life satisfaction and higher negative mental health problems for adolescent girls (Bor et al., 2014; Edbrooke-Childs, Deighton, & Wolpert, 2017; Lessof et al., 2016; The Children's Society, 2017). Though not tested statistically, previous research has reported approximately a one-point lower mean on a 10-point scale in overall life satisfaction in girls compared to boys (The Children's Society, 2017), and no research has explored sex differences in eudaimonic wellbeing indicators. I also found males had lower means on relatedness, autonomy and gratitude which could suggest there is nuance in sex differences across different components of wellbeing during adolescence. However, as the effect size across measures were small, I concluded that there were no meaningful differences in mean scores across sex or zygosity for our wellbeing indicators (Table 3.3).

Table 3.2 Descriptive statistics for the measures of wellbeing across the web and booklet data collection

Measure	Number of individuals	Number of complete twin pairs	% male	% MZ	Mean score (SD)	Min	Max	Skew	Kurtosis	Cronbach's Alpha
Web measures										
Life satisfaction	5315	2391	41.86	37.78	4.62 (0.62)	1.95	6	-0.67	0.71	0.86
Subjective happiness	5328	2402	41.87	37.76	5.22 (1.16)	1	7	-0.79	0.36	0.84
Hopefulness	5321	2394	41.83	37.77	4.71 (0.72)	1	6	-0.88	1.49	0.83
Gratitude	5322	2395	41.88	37.79	5.80 (0.85)	1	7	-0.81	0.75	0.74
Optimism	4649	2091	41.13	38.33	3.24 (0.71)	1	5	-0.18	0.05	0.77
Ambition	4647	2089	41.14	38.33	3.91 (0.68)	1	5	-0.48	0.09	0.75
Grit	4650	2092	41.14	38.32	3.29 (0.57)	1.50	5	0.22	-0.04	0.71
Curiosity	5310	2386	41.86	37.74	4.79 (0.91)	1.14	7	-0.20	-0.05	0.74
Health	5329	2402	41.87	37.77	3.00 (0.82)	0	4	-0.63	0.36	-
Booklet measures										
Life satisfaction	9623	4772	44.33	36.24	5.70 (1.06)	1	7	-1.12	1.08	0.86
Subjective happiness	9626	4775	44.36	36.22	5.12 (0.96)	1	7	-0.52	0.40	0.78
Relatedness	7486	3717	45.82	35.65	4.83 (0.85)	0.75	6	-0.88	0.65	0.84
Autonomy	7486	3717	45.82	35.65	3.98 (0.83)	0.43	6	-0.42	0.18	0.66
Competence	7482	3713	45.83	35.63	4.04 (0.93)	0	6	-0.25	-0.02	0.69
Meaning in life	7469	3701	45.75	35.64	5.12 (1.09)	1	7	-0.74	0.63	0.82
Trust	7362	3597	45.78	35.66	0.83 (0.37)	0	1	-1.78	1.17	-
Mindfulness	2140	1058	39.30	38.46	3.21 (0.87)	0.40	5	0.05	-0.26	0.76

Table 3.3 Means (SD) and ANOVA results for effect of sex and zygosity

	All (N = 1072-5462)	MZ (N = 892-1979)	DZ (N = 1424-3484)	Male (N = 956-2446)	Female (N = 1361-3016)	Sex p-value	Sex effect size	Zygosity p-value	Zygosity effect size
Life Satisfaction	-0.01 (1.01)	-0.01 (1.02)	-0.01 (1.00)	0.10 (0.98)	-0.09 (1.02)	9.38×10^{-12}	0.0085	0.99	2.43×10^{-8}
Subjective Happiness	0.00 (1.01)	0.01 (1.02)	-0.01 (1.01)	-0.02 (0.99)	0.01 (1.03)	0.39	0.00012	0.40	0.0001
Relatedness (b)	4.83 (0.85)	4.84 (0.88)	4.83 (0.84)	4.73 (0.84)	4.91 (0.86)	1.22×10^{-10}	0.011	0.75	2.69×10^{-5}
Autonomy (b)	3.98 (0.82)	3.99 (0.82)	3.97 (0.83)	3.93 (0.79)	4.01 (0.85)	0.002	0.0025	0.45	0.0002
Competence (b)	4.03 (0.93)	4.06 (0.93)	4.02 (0.93)	4.03 (0.90)	4.03 (0.96)	0.89	0.00001	0.12	0.0006
Gratitude (w)	5.79 (0.85)	5.81 (0.83)	5.78 (0.86)	5.67 (0.86)	5.88 (0.84)	7.53×10^{-10}	0.0141	0.39	0.0003
Optimism (w)	3.25 (0.71)	3.25 (0.71)	3.25 (0.71)	3.32 (0.68)	3.20 (0.73)	3.74×10^{-5}	0.0073	0.84	1.65×10^{-5}
Meaning in life (b)	5.12 (1.09)	5.13 (1.10)	5.11 (1.09)	5.16 (1.06)	5.09 (1.11)	0.047	0.0011	0.54	0.0001
Trust* (b)	0.83 (0.38)	0.83 (0.38)	0.83 (0.38)	0.86 (0.35)	0.80 (0.40)	1.46×10^{-6}	0.0063	1.00	4.69×10^{-10}
Hopefulness (w)	4.71 (0.70)	4.70 (0.72)	4.72 (0.69)	4.81 (0.68)	4.64 (0.71)	1.37×10^{-9}	0.0137	0.49	0.0002
Ambition (w)	3.92 (0.68)	3.93 (0.67)	3.90 (0.69)	3.96 (0.65)	3.88 (0.70)	0.007	0.0031	0.30	0.0005
Curiosity (w)	4.80 (0.91)	4.75 (0.90)	4.83 (0.91)	4.95 (0.88)	4.69 (0.91)	3.92×10^{-5}	0.0190	0.01	0.003
Grit (w)	3.30 (0.58)	3.34 (0.58)	3.27 (0.58)	3.24 (0.57)	3.34 (0.58)	1.06×10^{-12}	0.0073	0.04	0.002
Subjective health (w)	4.01 (0.81)	4.03 (0.82)	4.00 (0.80)	4.11 (0.79)	3.94 (0.82)	3.16×10^{-7}	0.0098	0.39	0.0003

Note: N refers to one randomly selected member of each twin pair to avoid non-independent observations; effect size=eta squared. (b) indicates booklet data collection. (w) indicates web data collection.
* Trust was measured using a dichotomous (yes/no) response. In the analyses here we have treated it as a numeric value (ranging from 0-1). Mean results for Life satisfaction and subjective happiness are standardized because these scores are composites across the web and booklet data collection.

3.1.4 Reliability estimates and sensitivity analyses

The internal reliability (Cronbach's alpha) was good for all measures, ranging 0.71 to 0.86. The test-retest reliability was calculated for life satisfaction (r = 0.64, 95% CI = 0.63 – 0.65) and subjective happiness (0.67, 0.66 – 0.68), with an average of 133 days between retests (range = 0 – 471 days). This shows good test-retest reliability given the six-month time lag and the change in the scale used to measure life satisfaction. It was only possible to calculate test-retest reliability for these two measures because only these measures were collected both online and in the booklet.

For some of the analysis in this thesis (Chapters 4, 5 and 7), when participants had responses for both web and booklet measures, the mean score was taken. These analyses are presented in Table 3.4, along with the means for individuals that completed the booklet only, individuals that completed the booklet and web data collection, individuals that completed the web only and individuals that completed the booklet and web data collection. I performed sensitivity analyses to test for differences in the mean scores across the web and booklet. I used one randomly selected twin from each twin pair to avoid non-independent observations. For both subjective wellbeing indicators, I created subgroups of individuals who had either completed the booklet only, the web only or both the booklet and the web. For the 'both' group, I took a mean score across both forms of data collection. I then assessed the difference in mean scores between the subgroups of booklet and web, booklet and both, and web and both (Table 3.4). I expected to find significant differences between subgroups even if the absolute difference was small because the TEDS sample is large (for Ns see Table 3.2), the web and the booklet were collected on average six months apart, and life satisfaction was collected using two different scales. Consequently, when a *t*-

test indicated a significant difference, I calculated cohen's d, and accepted any differences that did not reach the threshold of a 'small effect' (d > |0.20|). For life satisfaction, we found significant differences between the web and the booklet and the web and both. For subjective happiness, we found a significant difference between the booklet and both (Table 3.4). As expected, the effect size of the difference was higher for life satisfaction (d = 0.13 and 0.16). However, because no effect size reached the threshold of a small effect (0.20), I concluded there were no meaningful differences between the mean life satisfaction or subjective happiness scores for participants who provided data on only the web, only the booklet or on both.

Table 3.4 Sensitivity analysis for mean scores across data collection methods in TEDS for life satisfaction and subjective happiness

Comparison	***t*-test**		**Cohen's D**	
Life Satisfaction				
Booklet vs. web	$t(935.89) = 2.89, p = 0.004$		0.13	
Booklet vs. both	$t(4645.5) = 0.51, p = 0.61$		0.01	
Both vs. web	$t(943.88) = 3.17, p = 0.02$		0.16	
Subjective Happiness				
Booklet vs. web	$t(835.5) = -1.39, p = 0.17$		0.07	
Booklet vs. both	$t(4245.7) = -1.73, p = 0.08$		-0.05	
Both vs. web	$t(928.3) = 0.43, p = 0.67$		0.02	
	Booklet scores		**Web scores**	
	Completed booklet only	**Booklet score, completed both**	**Completed web only**	**Web score, completed both**
Life Satisfaction				
Standardised mean score (SD)	-0.001 (1.02)	-0.009 (0.99)	-0.14 (1.09)	0.04 (0.96)
N	2811	2004	654	2004
Subjective Happiness				
Mean score (SD)	5.12 (0.95)	5.11 (0.99)	5.19 (1.23)	5.22 (1.15)
N	2804	2013	651	2013

Note. N refers to one randomly selected twin from each twin pair. Booklet uses data from one randomly selected twin from each with pair that completed the booklet measure only. Web refers to one randomly selected twin from each twin pair that completed the web measure only. Both refers to one randomly selected twin from each twin pair that completed both the web and booklet.

3.2 Statistical procedures

This section has two parts: twin modelling and Principal Components Analysis. The twin modelling section describes the models used to decompose the variation in a trait into genetic and environmental influences, and extensions of this basic model. The Principal Components Analysis section describes the method and outlines the theoretical decisions concerning rotation, component extraction and component loadings.

3.2.1 Twin model fitting

Twin modelling is used to decompose the total variance of a trait into genetic and environmental influences, using the assumptions of twin designs (described in Chapter 2). All twin analysis uses observed differences in the correlations between MZ twins (rMZ) and DZ twins (rDZ) for a given trait to estimate the proportion of variation in the trait that is due to genetic (additive, A or non-additive, D), and environmental (shared, C or nonshared, E) influences. Consequently, twin modelling requires variance-covariance matrices derived from the raw data. I explain how the variance-covariance matrices are constructed in Appendix 3.3. Before we estimate the decomposed variance of a trait, we first calculate saturated models that estimate the total variance and covariance in the data with the maximum number of free parameters. This can be achieved using a Cholesky or Gaussian specification, which model the data differently but arrive at the same estimates (explained in more detail in Appendix 3.3 and below). We use the saturated model to test the assumptions of equal means and variances across twin order and twin zygosity. Once we have tested the assumption of equal means and variances, we equate the means and variances across twin order and zygosity. We then use one overall mean in the twin models to decompose the variance into genetic and environmental influences. We also account for variation due to age and sex, so that our results represent the decomposed variance for the average age across both males and females (method described in Appendix 3.3).

Further detail on the saturated model, equating the means and variances and accounting for age and sex is provided in Appendix 3.3. It is also worth noting that the twin correlations described here are intraclass correlations because we have equated the means and variances across twin order to account for the random allocation of each twin from a twin pair as ‘Twin 1’ or ‘Twin 2’ (see Appendix 3.3 for more detail). Intraclass correlations can be interpreted similarly to a standard correlation, where a higher positive intraclass correlation indicates more similarity within twin pairs than between twin pairs. Here, I start by describing the basic univariate model used to estimate the proportion of the total variance explained by genetic and environmental influences. I then describe extensions of the univariate model to threshold liability models (for categorical data) and bivariate models (for two traits).

3.2.1.1 Decomposing the variance: the univariate ACE model

Twin modelling is used to decompose the total variance of a trait into four components: additive genetic influences, represented by A; non-additive genetic influences, represented by D; shared environmental influences, represented by C; and nonshared environmental influences, represented by E. This is represented by:

$$V_T = V_A + V_D + V_C + V_E$$

where the total variance for a trait, V_T, is the sum of additive genetic influences (V_A), non-additive genetic influences (V_D), shared environmental influences (V_C), and nonshared environmental influences (V_E). We estimate heritability (h^2, also represented by a^2), which is the proportion of the phenotypic variance explained by additive genetic influences (Falconer, 1975):

$$h^2 = \frac{V_A}{V_T}$$

Broad sense heritability (H^2) is the proportion of the phenotypic variance explained by additive (A) and non-additive (D) genetic influences:

$$H^2 = \frac{V_A + V_D}{V_T}$$

The proportion of the phenotypic variance explained by shared environmental influences (c^2) and the proportion by nonshared environmental influences (e^2) are calculated by:

$$c^2 = \frac{V_C}{V_T}$$

$$e^2 = \frac{V_E}{V_T}$$

Twin modelling relies on assumptions of the proportion of the genetic and environmental similarity between MZ and DZ twins. First, we assume MZ twins share 100% of their additive genetic influences (V_A), and DZ twins share 50% ($\frac{1}{2}V_A$). Second, we assume MZ twins share 100% of the non-additive genetic influences (V_D), and DZ twins share 25% ($\frac{1}{4}V_D$). Third, we assume both MZ and DZ twins share 100% of their shared environment (V_C). Finally, we assume that nonshared environmental influences (V_E) do not contribute to the similarity between MZ or DZ twins. The difference between MZ twins and DZ twins is half the additive genetic influences, and three quarters of the non-additive genetic influences ($0.5V_A + 0.75V_D$). By applying these assumptions, we can estimate heritability (a^2), shared environmental influences (c^2), and nonshared environmental influences (e^2), by substituting rMZ, rDZ and the trait variance (standardsised to 1) into Falconer's formula (1975):

$$rMZ = a^2 + c^2$$

$$rDZ = \frac{1}{2}a^2 + c^2$$

$$a^2 + c^2 + e^2 = 1$$

We can calculate the heritability estimate (a^2) by subtracting the correlation between DZ twins (rDZ) from the correlation between MZ twins (rMZ):

$$rMZ - rDZ = (a^2 + c^2) - (\frac{1}{2}a^2 + c^2)$$

$$rMZ - rDZ = a^2 + c^2 - \frac{1}{2}a^2 - c^2$$

$$rMZ - rDZ = \frac{1}{2}a^2$$

$$a^2 = 2(rMZ - rDZ)$$

This shows that the heritability estimate is twice the difference in the correlation between MZ and DZ twins. We can calculate the shared environmental estimate (c^2) by subtracting the heritability estimate from the MZ correlation:

$$rMZ = a^2 + c^2$$

$$rMZ = 2(rMZ - rDZ) + c^2$$

$$c^2 = rMZ - 2(rMZ - rDZ)$$

We can calculate the nonshared environmental estimate (e^2) by subtracting the MZ correlation from 1, assuming we have standardised the trait variance to 1:

$$a^2 + c^2 + e^2 = 1$$

$$[2(rMZ - rDZ)] + [rMZ - 2(rMZ - rDZ)] + e^2 = 1$$

$$2rMZ - 2rDZ + rMZ - 2rMZ + 2rDZ + e^2 = 1$$

$$rMZ + e^2 = 1$$

$$e^2 = 1 - rMZ$$

Using the intraclass correlations between MZ twins and DZ twins, and the trait variance, we can estimate up to three unknown parameters at once (A, C and E or A, D and E) because we have three observed statistics: the correlation between MZ twins (rMZ), the correlation between DZ twins (rDZ) and the total trait variance (V_T), which is standardised to 1 in our variance-covariance matrix. We must estimate nonshared environmental influences (E) in every model because E includes measurement error, and it is very unlikely we will be estimating a model free from measurement error. The presence of genetic influences on a trait is indicated when the correlation between MZ twins is greater than between DZ twins (rMZ > rDZ). If the phenotypic correlation is the same for MZ and DZ twins (rMZ = rDZ), then the variation in the trait would be entirely due to environmental influences (Rijsdijk & Sham, 2002). If the correlation between MZ twins is greater than twice that of DZ twins (rMZ > 2rDZ), it indicates the presence of non-additive genetic influences (D). In this case, we would apply the above assumptions to Falconer's (1975) formula to estimate the dominant effects (d^2) instead of the shared environment (c^2):

$$rMZ = a^2 + d^2$$

$$rDZ = \frac{1}{2}a^2 + \frac{1}{4}d^2$$

$$a^2 + d^2 + e^2 = 1$$

In the example data provided in Appendix 3.3, the correlation between MZ twins was 0.73, and the correlation between DZ twins was 0.55. From these correlations, we would predict the presence of additive genetic influences but not dominant genetic influences, and we could calculate estimates of a^2, c^2, e^2 by solving the following equations simultaneously:

$$a^2 = 2(rMZ - rDZ)$$

$$a^2 = 2(0.73 - 0.55)$$

$$a^2 = 0.36$$

$$c^2 = rMZ - a^2$$

$$c^2 = 0.73 - 0.36$$

$$c^2 = 0.37$$

$$e^2 = 1 - rMZ$$

$$e^2 = 1 - 0.73$$

$$e^2 = 0.27$$

From this example, we would conclude that 36% of the population variation in the trait is due to additive genetic effects, 37% is due to shared environmental effects, and 27% is due to nonshared environmental effects. We use OpenMx to estimate these parameters, which allows us to control for covariates (such as age and sex) and calculates confidence intervals. The parameter estimates for the proportion of variance can be calculated in OpenMx using both Cholesky and Gaussian specifications, as shown below.

3.2.1.2 Specifying the univariate ACE model

By extending the Cholesky specification described in Appendix 3.3, we can estimate the A, C and E path coefficients. As we decompose the variance (V) into A, C and E, we have three latent variables (or model parameters). This is visualised in the path diagram in Figure 3.1. We model MZ and DZ twins separately, because we expect the covariance between MZ twins to be higher than DZ twins. Following the legitimate paths (path tracing is explicitly outlined in Appendix 3.3 and Figure 3.2) for Twin 1, the variance in Twin 1 is $a_{11}^2 + c_{11}^2 + e_{11}^2$, the variance in Twin 2 is $a_{21}^2 + a_{22}^2 + c_{21}^2 + c_{22}^2 + e_{21}^2 + e_{22}^2$, and the covariance between the twins is $a_{11}a_{21} + c_{11}c_{21}$.

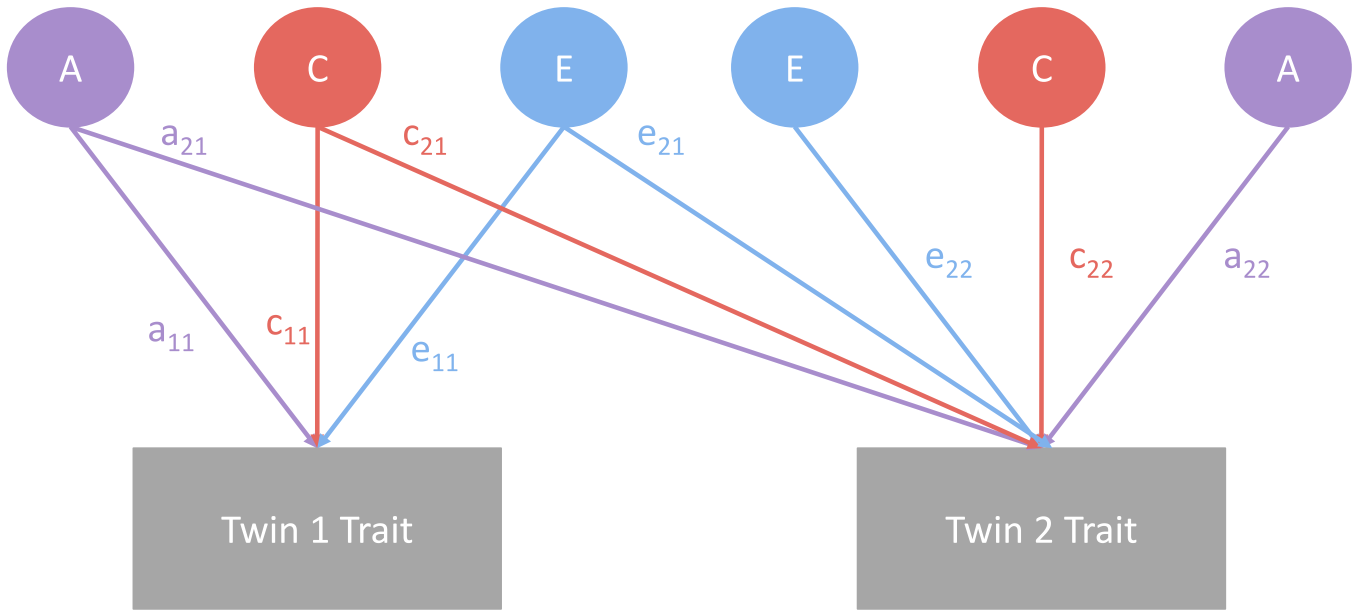


Figure 3.1 Path diagram of the Cholesky univariate ACE model. A, C, and E represent the genetic, shared and nonshared environmental influences respectively. Single-headed arrows show a causal path, indicating that the latent variables (A, C and E; in circles) causally influence the observed twin scores (in grey boxes). Lower case a, c and e represent the path coefficients for the proportion of variance explained by genetic, shared and nonshared environmental influences respectively. Subscript 11 indicates the variance explained for Twin 1, subscript 21 indicates the variance in Twin 2 explained by the variance in Twin 1,

and subscript 22 indicates the unique variance in Twin 2 that is not explained by the variance in Twin 1. The variance and covariance can be traced following the legitimate paths. The variance in Twin 1 is calculated by $a_{11} \times 1 \times a_{11} + c_{11} \times 1 \times c_{11} + e_{11} \times 1 \times e_{11} = a_{11}^2 + c_{11}^2 + e_{11}^2$. The variance in Twin 2 is calculated by $a_{21} \times 1 \times a_{21} + a_{22} \times 1 \times a_{22} + c_{21} \times 1 \times c_{21} + c_{22} \times 1 \times c_{22} + e_{21} \times 1 \times e_{21} + e_{22} \times 1 \times e_{22} = a_{21}^2 + a_{22}^2 + c_{21}^2 + c_{22}^2 + e_{21}^2 + e_{22}^2$. The covariance between the twin groups is calculated by $a_{11} \times 1 \times a_{21} + c_{11} \times 1 \times c_{21} = a_{11}a_{21} + c_{11}c_{21}$. Separate path diagrams are used for MZ and DZ twins, because we expect the genetic parameters to differ.

Most of the time, we do not want to model a Cholesky decomposition because it calculates separate estimates for Twin 1 and Twin 2, but the allocation of twins to Twin 1 or Twin 2 is random. Instead, we are more interested in the proportion of the total variance across both twins that is explained by genetic (A), shared (C) and nonshared (E) environmental influences. Consequently, we can convert the Cholesky decomposition into a Gaussian ACE model by estimating one path for each of A, C and E. The Gaussian model is displayed in Figure 3.2b, with path tracing added in black dashed arrows. As shown in Figure 3.2a, the variance in Twin 1 (or Twin 2) is calculated in the same way as the Twin 1 variance in the Cholesky decomposition, which results in $a^2 + c^2 + e^2$. The covariance between MZ twins is estimated by $a^2 + c^2$, and DZ twins is $0.5a^2 + c^2$, which is calculated by path tracing as shown by the black dashed arrows in Figure 3.3b. This results in the same equations as Falconer’s formula (1975).

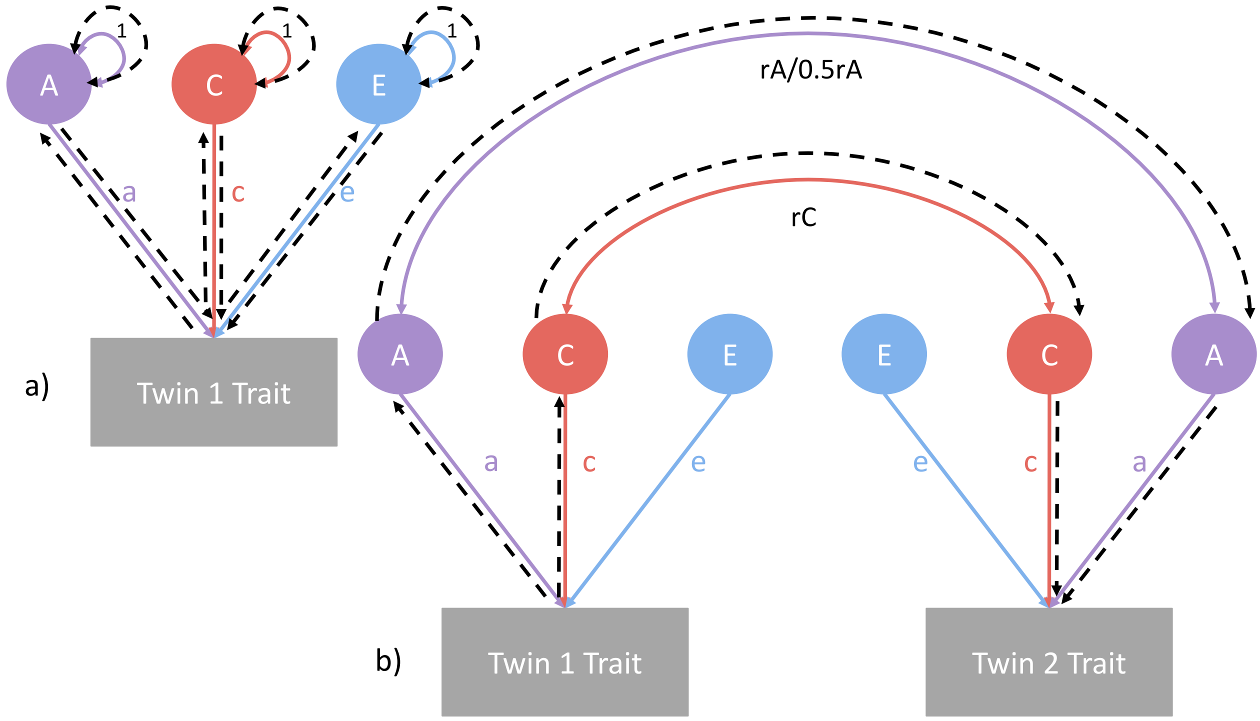


Figure 3.2 Path diagram of the basic twin model: Gaussian ACE univariate model, with path tracing represented by black dashed arrows. A, C, and E represent the genetic, shared and nonshared environmental influences respectively. Single-headed arrows show a causal path, indicating that the latent variables (A, C and E; in circles) causally influence the observed twin scores (in grey boxes). Lower case letters a, c, and e represent the genetic, shared and nonshared environmental partial regression coefficients, respectively. a) The variance in Twin 1 (or Twin 2) is calculated by $\boldsymbol{a_{11}} \times \mathbf{1} \times \boldsymbol{a_{11}} + \boldsymbol{c_{11}} \times \mathbf{1} \times \boldsymbol{c_{11}} + \boldsymbol{e_{11}} \times \mathbf{1} \times \boldsymbol{e_{11}} = \boldsymbol{a_{11}^2} + \boldsymbol{c_{11}^2} + \boldsymbol{e_{11}^2}$. b) Double-headed arrows represent covariance between two variables. The correlation between the genetic influences for MZ twins (rMZ) is 1, and for DZ twins (rDz) is 0.5. The correlation between the shared environmental influences for both MZ and DZ twins is 1. There is no correlation between the nonshared environmental influences for both MZ and DZ twins. The covariance between MZ twins is $\boldsymbol{a} \times \mathbf{1} \times \boldsymbol{a} + \boldsymbol{c} \times \mathbf{1} \times \boldsymbol{c} = \boldsymbol{a^2} + \boldsymbol{c^2}$. The covariance between DZ twins is $\boldsymbol{a} \times \mathbf{0.5} \times \boldsymbol{a} + \boldsymbol{c} \times \mathbf{1} \times \boldsymbol{c} = \mathbf{0.5}\boldsymbol{a^2} + \boldsymbol{c^2}$.

In OpenMx, we specify the univariate ACE model by creating matrices to store the paths for each variance component and apply the same formulas described in Appendix 3.3 to estimate the variance-covariance matrices. We model the variance in A, C and E separately (e.g. `a%*%t(a)`, where a is a matrix of the genetic path coefficient), then add the matrices together to calculate the total variance (V_T) in the trait ($V_T = V_A + V_C + V_E$). We standardise the path coefficients by multiplying the path coefficient by the total trait variance using a variation of the Cholesky formula (e.g. to standardise the genetic path coefficient: `a%*%solve(sqrt(I*V))`), and we standardise the variance estimates by dividing each variance component by the total variance (e.g. the genetic variance is standardised as $a^2 = \frac{V_A}{V_T}$). Finally, we create separate variance-covariance matrices for MZ and DZ twins and specify that the covariance between MZ twins is calculated by $a^2 + c^2$, and the covariance in DZ twins is calculated by $0.5a^2 + c^2$. We estimate one variance across all twins and assume equal variance across twin order and zygosity. The resulting variance-covariance matrices for MZ and DZ twins are:

$$\mathrm{MZ} = \begin{array}{c c} & \begin{array}{cc} \text{Twin 1} & \text{Twin 2} \end{array} \\ \begin{array}{c} \text{Twin 1} \\ \text{Twin 2} \end{array} & \begin{bmatrix} a^2 + c^2 + e^2 & a^2 + c^2 \\ a^2 + c^2 & a^2 + c^2 + e^2 \end{bmatrix} \end{array}$$

$$\mathrm{DZ} = \begin{array}{c c} & \begin{array}{cc} \text{Twin 1} & \text{Twin 2} \end{array} \\ \begin{array}{c} \text{Twin 1} \\ \\ \text{Twin 2} \end{array} & \begin{bmatrix} a^2 + c^2 + e^2 & \frac{1}{2}a^2 + c^2 \\ \frac{1}{2}a^2 + c^2 & a^2 + c^2 + e^2 \end{bmatrix} \end{array}$$

The ACE model is an *identified* model, which means there are only one set of possible parameters that will give the correct estimates for the MZ and DZ variance-covariance matrices. Consequently, we can refer to the univariate ACE model as a *saturated* model, because there is only one possible solution, which has been modelled exactly. This assumes that the twin covariances are both positive (meaning there is more variation between twin pairs than within twin pairs) and the MZ covariance is larger than the DZ covariance.

Using the example data in Appendix 3.3, if rMZ was 0.73, and rDZ was 0.55, the only solution would be the same as the previous example for solving simultaneous equations using Falconer's formula, where a^2= 0.36, c^2 = 0.37 and e^2 = 0.27. The variance-covariance matrices for MZ and DZ twins would be:

$$\mathrm{MZ} = \begin{bmatrix} a^2 + c^2 + e^2 & a^2 + c^2 \\ a^2 + c^2 & a^2 + c^2 + e^2 \end{bmatrix} = \begin{bmatrix} 0.36 + 0.37 + 0.27 & 0.36 + 0.37 \\ 0.36 + 0.37 & 0.36 + 0.37 + 0.27 \end{bmatrix} = \begin{bmatrix} 1 & 0.73 \\ 0.73 & 1 \end{bmatrix}$$

$$\mathrm{DZ} = \begin{bmatrix} a^2 + c^2 + e^2 & \frac{1}{2}a^2 + c^2 \\ \frac{1}{2}a^2 + c^2 & a^2 + c^2 + e^2 \end{bmatrix} = \begin{bmatrix} 0.36 + 0.37 + 0.27 & 0.18 + 0.37 \\ 0.18 + 0.37 & 0.36 + 0.37 + 0.27 \end{bmatrix} = \begin{bmatrix} 1 & 0.55 \\ 0.55 & 1 \end{bmatrix}$$

OpenMx finds the best-fitting model by substituting values for the overall mean (M) and the A, C and E path coefficients (a, c, and e), then estimating the variance-covariance matrix. For example, a first estimate for the example data may be M = 4, a = 0.4, c = 0.3, and e = 0.3. From the estimated variance components, OpenMx would estimate variance-covariance matrices as:

$$\mathrm{MZ} = \begin{bmatrix} 0.4 + 0.3 + 0.3 & 0.4 + 0.3 \\ 0.4 + 0.3 & 0.4 + 0.3 + 0.3 \end{bmatrix} = \begin{bmatrix} 1 & 0.7 \\ 0.7 & 1 \end{bmatrix}$$

$$\mathrm{DZ} = \begin{bmatrix} 0.4 + 0.3 + 0.3 & 0.2 + 0.3 \\ 0.2 + 0.3 & 0.4 + 0.3 + 0.3 \end{bmatrix} = \begin{bmatrix} 1 & 0.5 \\ 0.5 & 1 \end{bmatrix}$$

This result would then be evaluated and improved on during the model-fitting process. New combinations of parameters would be estimated until the best-fitting model was found. This process is known as *optimisation*.

Once the best-fitting model for the univariate ACE model has been found, we can compare the model fit statistics to nested models, which have fewer parameters. For example, we could compare an ACE model to an AE model to explain our data with a more parsimonious model. We can perform this in OpenMx by creating a submodel of the ACE model that constrains parameter C to zero:

```
AEModel <- omxSetParameters(AEModel, labels=c("c11"), free = F,
                            values = 0)
```

This is similar to testing the assumption of equal means and variances across twin order and zygosity (described in Appendix 3.3). The submodels will never fit the data better than the saturated ACE model (which always fit the observed data exactly), but if the AE model does not fit significantly worse according to the fit statistics, then we could conclude that shared environmental influences (C) do not explain a substantial proportion of the variance of a given trait, and we would choose to model our data with an AE model.

3.2.1.3 Extensions to the basic twin model

In this thesis, the univariate ACE model is extended as a liability threshold model, a bivariate model and an MZ differences model (this is explained in detail in Chapter 6). Other extensions not included here are multivariate models and heterogeneity models including sex limitation models.

As 14 wellbeing indicators are included in this thesis, it might be considered that a single multivariate model could be used to calculate the shared A, C and E across the measures. However, this would be difficult to optimise and challenging to interpret. Instead, I ran a series of bivariate models and extracted the genetic and environmental correlations.

Incorporating this with Principal Components Analysis (PCA, described below) allows visualisation of the results and highlights clusters of measures that are more strongly related for genetic or environmental reasons (Davis & Plomin, 2010).

3.2.1.3.1 Liability threshold model

A liability threshold model estimates the underlying distribution of the trait liability for measures with dichotomous responses. In this thesis, we used a threshold liability model for trust, which had 'yes' or 'no' responses. We assume that trust is normally distrusted across the population, and that our dichotomous response reflects a bivariate normal distribution across the twin pairs. Based on the proportion of individuals that responded 'yes' and the proportion that responded 'no', we can estimate where the threshold (or cut-off point) between responses lies on the normal distribution. We first create a contingency table for twins that are concordant (responded the same way) and discordant. For example, the contingency table for trust would be:

		Twin 2	
		Yes	No
Twin 1	Yes	Concordant: yes	Discordant
	No	Discordant	Concordant: no

We can then use probabilities to estimate the twin correlations based on the proportions of concordant yes, discordant and concordant no twin pairs, and the threshold we allocated to the response. OpenMx estimates the correlations using numerical integration of the bivariate normal distribution over the two liabilities, which are the probability that both twins lie above the threshold (e.g. both twins are concordant yes). This is estimated using optimisation as in the univariate model, and the estimated correlation is the most likely based on the data provided. The correlations for trust are tetrachoric, because we have one threshold that separates the 'yes' and 'no' responses. We estimate the liability for MZ and DZ twins separately, and decompose the variation in the liability of trust into A, C and E. Consequently, we provide estimates of the liability in trust, as demonstrated in Figure 3.3.

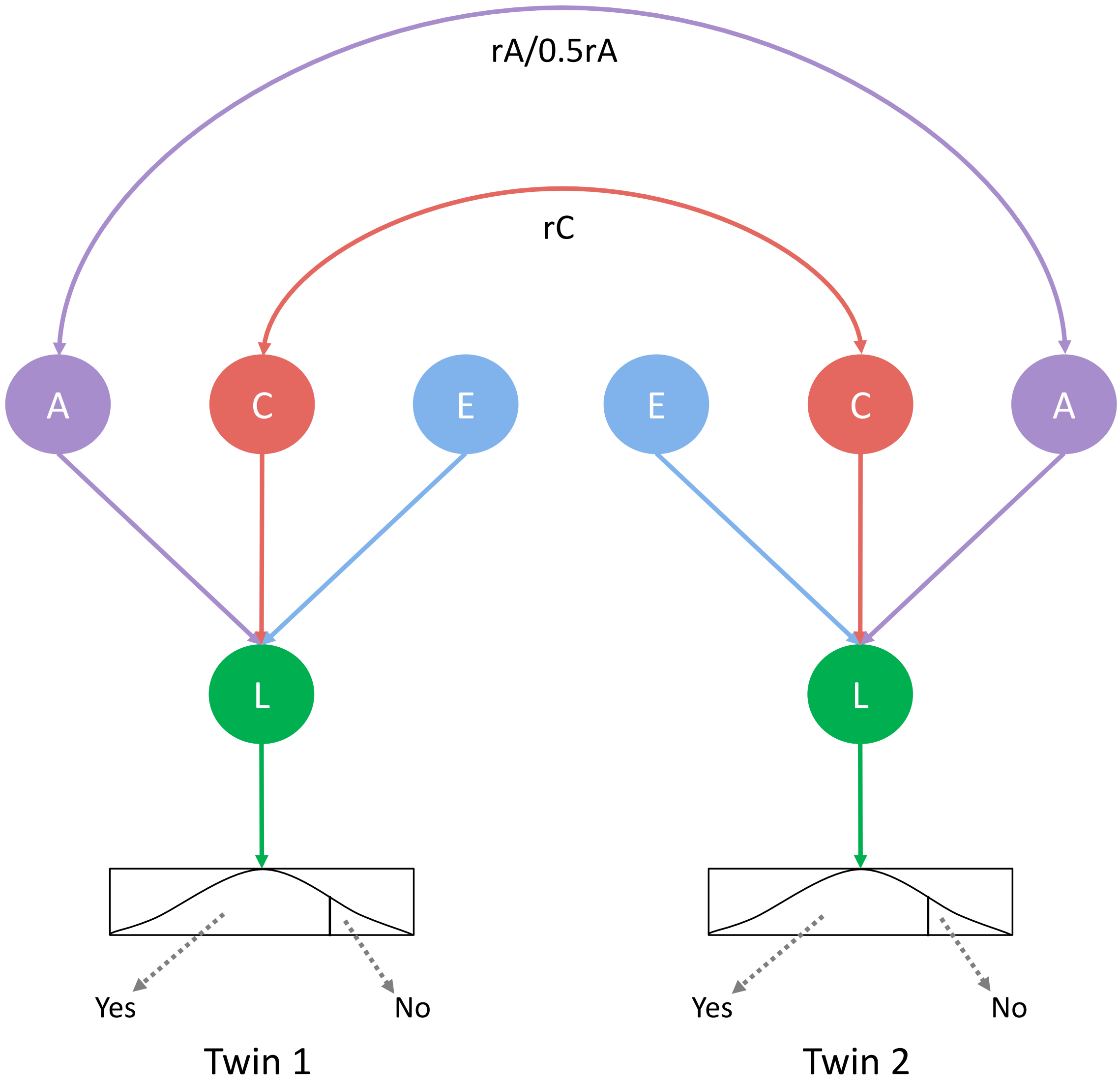


Figure 3.3 A visual representation of the threshold liability model. This is not a path diagram, and instead shows the principles of the threshold liability model. A, C and E (in circles) represent the latent genetic, shared and nonshared environmental components. The liability estimate is represented by L in the green circle. Decomposition of the variance into

A, C and E is applied to the liability to the trait. This represents the location of the threshold between the dichotomous response 'yes' and 'no' on a normal distribution.

We can test that the thresholds are equal across twin order and zygosity by creating submodels of the full model, in exactly the same way as the univariate model. For example, to equate the thresholds for MZ twins in a submodel, we would use the following code:

```
Sub1Model <- omxSetParameters(Sub1Model, labels=c("Tmz1","Tmz2"),
                    newlabels="Tmz1")
```

In this code, the threshold for MZ Twin 1 (`Tmz1`) and MZ Twin 2 (`Tmz2`) are both relabelled as `Tmz1`, which uses one threshold across all MZ twins, regardless of twin order.

After testing the assumptions of equal thresholds, we can run the liability threshold ACE model, as shown in Figure 3.3. This is identical to the univariate ACE model, except we explicitly constrain the total variance of the liability ($varL = a^2 + c^2 + e^2$) to equal 1 using the function `mxConstraint()`.

3.2.1.4 Bivariate ACE model

Bivariate models allow us to estimate the degree to which the components that explain the variance in one trait also explain the variance in another trait. For example, a bivariate ACE model of happiness and gratitude would estimate the extent that the genetic (A), shared environmental (C) and nonshared environmental (E) influences on happiness also influence gratitude.

Similar to the twin estimates in the univariate Cholesky model, the bivariate Cholesky decomposition provides complete estimates of A, C and E for the first trait added to the model, then decomposes how much variance of the first trait accounts for variance of A, C and E in the second trait, then estimates the remaining variance in the second trait. The Cholesky decomposition is useful when there is reason to believe one trait should come before a second trait, such as in a longitudinal study of happiness, where happiness has been measured first in childhood and second in adolescence. The Cholesky model is displayed in Figure 3.4, which shows a traceable path from the first trait to the second trait. The semi-transparent path displays the traceable path across the twin pair, although this is not usually included on path diagrams of the Cholesky decomposition. The total variance in the first trait ('Twin 1 Trait 1' in Figure 3.4) can be calculated by following the legitimate paths. This is represented algebraically by: $a_{11} \times 1 \times a_{11} + c_{11} \times 1 \times c_{11} + e_{11} \times 1 \times e_{11} = a_{11}^2 + c_{11}^2 + e_{11}^2$. The total variance in the second trait ('Twin 1 Trait 2' in Figure 3.4) is calculated in the same way, but includes the shared variance with the first trait: $a_{21}^2 + a_{22}^2 + c_{21}^2 + c_{22}^2 + e_{21}^2 + e_{22}^2$.

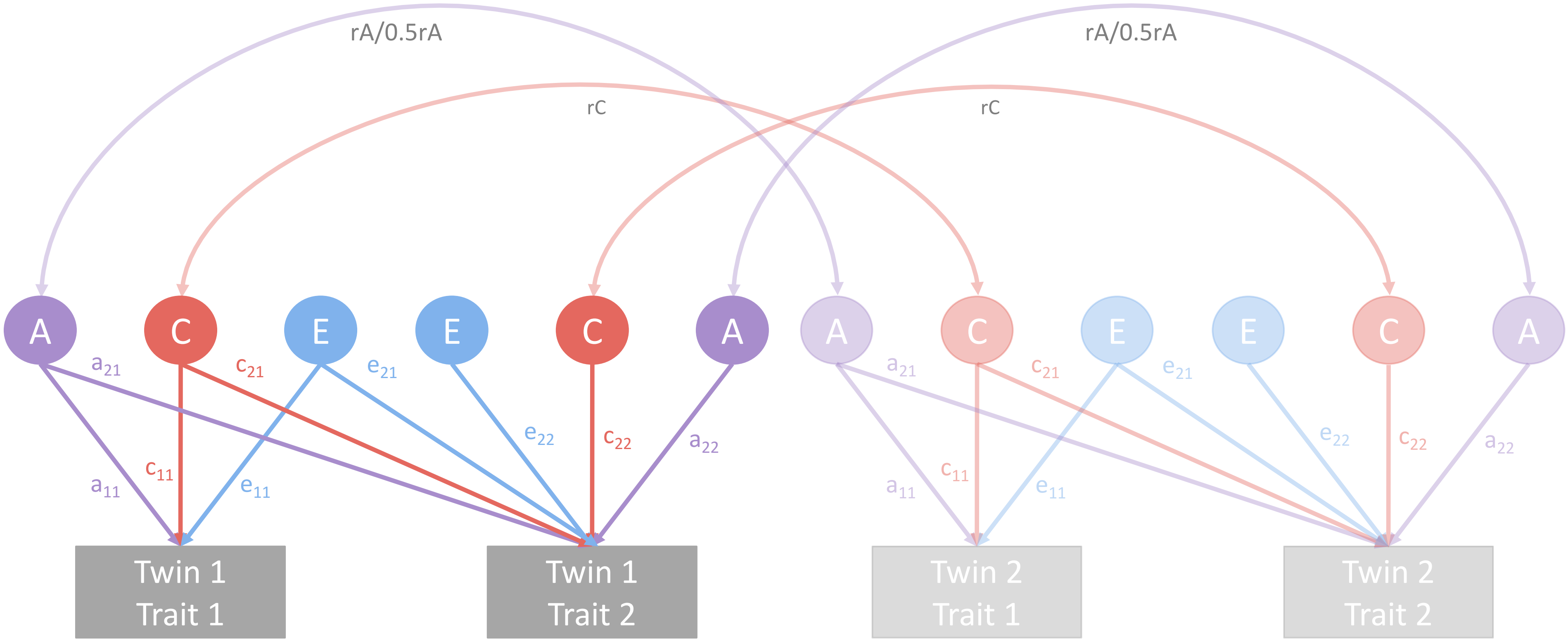


Figure 3.4 Path diagram of the Cholesky decomposition. The observed twin scores are displayed in the grey boxes, and the latent variance components (A, C and E) are displayed in circles. Lower case letters a, c, and e represent the genetic, shared and nonshared environmental partial regression coefficients, respectively. The subscript of lower case a, c, and e represent the twin number and trait number. For example, $\boldsymbol{a_{11}}$ indicates the genetic partial regression coefficient for Twin 1, Trait 1, and $\boldsymbol{e_{12}}$ represents the nonshared environmental partial regression coefficient for Twin 1, Trait 2. The variance and twin covariance for each trait and the twin covariance across the traits can be calculated by adding all the legitimate paths. For example, the variance for Trait 1 would be all the legitimate paths for 'Twin 1 Trait 1' (this is identical to 'Twin 2 Trait 1'): $\boldsymbol{a_{11} \times 1 \times a_{11} + c_{11} \times 1 \times c_{11} + e_{11} \times 1 \times e_{11} = a_{11}^2 + c_{11}^2 + e_{11}^2}$ and the variance for Trait 2 is all the legitimate paths for 'Twin 1 Trait 2': $\boldsymbol{a_{21} \times 1 \times a_{21} + a_{22} \times 1 \times a_{22} + c_{21} \times 1 \times c_{12} + c_{22} \times 1 \times c_{22} + e_{21} \times 1 \times e_{21} + e_{22} \times 1 \times e_{22} = a_{21}^2 + a_{22}^2 + c_{21}^2 + c_{22}^2 + e_{21}^2 + e_{22}^2}$. The covariance for Trait 1 is all the legitimate paths from 'Twin 1 Trait 1' to 'Twin 2 Trait 1'. For MZ twins this is: $\boldsymbol{a_{11} \times 1 \times a_{11} + c_{11} \times 1 \times c_{11} = a_{11}^2 + c_{11}^2}$. The covariance between DZ twins is $\boldsymbol{a_{11} \times 0.5 \times a_{11} + c_{11} \times 1 \times c_{11} = 0.5a_{11}^2 + c_{11}^2}$. The covariance for Trait 2 is calculated in the same way, following all the legitimate paths from 'Twin 1 Trait 2' to 'Twin 2 Trait 2'. For MZ twins this is $\boldsymbol{a_{22} \times 1 \times a_{22} + c_{22} \times 1 \times c_{22} = a_{22}^2 + c_{22}^2}$, and for DZ twins is $\boldsymbol{a_{22} \times 0.5 \times a_{22} + c_{22} \times 1 \times c_{22} = 0.5a_{22}^2 + c_{22}^2}$. The cross-twin cross-trait covariance is calculated using all the legitimate paths from 'Twin 1 Trait 1' to 'Twin 2 Trait 2' (which is identical to 'Twin 2 Trait 1' to 'Twin 1 Trait 2'). For MZ twins this is $\boldsymbol{a_{11} \times 1 \times a_{21} + c_{11} \times 1 \times c_{21} = a_{11}a_{21} + c_{11}c_{21}}$, and for DZ twins is $\boldsymbol{a_{11} \times 0.5 \times a_{21} + c_{11} \times 1 \times c_{21} = 0.5(a_{11}a_{21}) + c_{11}c_{21}}$.

A Cholesky decomposition can be converted into the mathematically equivalent correlated factors solution, which represents an extension of the univariate Gaussian decomposition. The correlated factors solution provides A, C and E estimates for each of the traits, the aetiological correlations (the correlation between the genetic (rA), shared environmental (rC), and nonshared environmental (rE) influences for each trait), and the proportion of the phenotypic correlation between the traits that is due to A, C and E (Loehlin, 1996). It is used when there is no *apriori* reason to order the traits. Because the order of our 14 wellbeing indicators is arbitrary, we converted the Cholesky decomposition into a correlated factors solution.

In OpenMx, we extend the univariate model to a bivariate model by increasing the size of the matrices to include a second trait, as shown for the variance-covariance matrices (modelled separately for MZ and DZ twins):

$$
\begin{array}{ll}
 & \begin{array}{cccc} \text{Twin 1} & & \text{Twin 2} & \\ \text{Trait 1} & \text{Trait 2} & \text{Trait 1} & \text{Trait 2} \end{array} \\
\begin{array}{ll} \text{Twin 1} & \begin{array}{l}\text{Trait 1}\\ \text{Trait 2}\end{array} \\ \text{Twin 2} & \begin{array}{l}\text{Trait 1}\\ \text{Trait 2}\end{array} \end{array} &
\begin{bmatrix}
Var_{Tr1} & & & \\
Cov_{(Tr1,Tr2)} & Var_{Tr2} & & \\
Cov_{xTw\,Tr1} & xTwxTr & Var_{Tr1} & \\
xTwxTr & Cov_{xTw\,Tr2} & Cov_{(Tr1,Tr2)} & Var_{Tr2}
\end{bmatrix}
\end{array}
$$

The only rule is that the order the variables enter the model in OpenMx must follow: Twin 1 Trait 1, Twin 1 Trait 2, Twin 2 Trait 1, Twin 2 Trait 2 (i.e. all of the twin 1 variables first, followed by all of the twin 2 variables).

As before, we equate the means and variances across twin order and zygosity. Decomposing the variance within each trait into A, C and E components is exactly the same as the univariate model. For example, we create a lower matrix for the path coefficients, where the first row and column are Trait 1, and the second row and column are Trait 2:

$$a = \begin{bmatrix} a_{11} & 0 \\ a_{21} & a_{22} \end{bmatrix}$$

$$c = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}$$

$$e = \begin{bmatrix} e_{11} & 0 \\ e_{21} & e_{22} \end{bmatrix}$$

where a_{11} is the path coefficient to Trait 1, a_{22} is the path coefficient to Trait 2, and $a_{21}$is the path coefficient from the variance in Trait 1 to Trait 2. We then compute the variance and covariance components using the same formula as before (`a%*%t(a)`). For example, the variance for the genetic component is:

$$A = \begin{bmatrix} a_{11} & 0 \\ a_{21} & a_{22} \end{bmatrix} * \begin{bmatrix} a_{11} & a_{21} \\ 0 & a_{22} \end{bmatrix} = \begin{bmatrix} a_{11}^2 & a_{21}a_{22} \\ a_{21}a_{22} & a_{21}^2 a_{22}^2 \end{bmatrix}$$

where a_{11}^2 is the genetic component of variance for Trait 1 (Var_{Tr1a}), $a_{21}a_{22}$ is the genetic component of covariance between the traits ($Cov_{(Tr1,Tr2)a}$), and $a_{21}^2 a_{22}^2$ is the genetic component of variance for Trait 2 (Var_{Tr2a}). This can be confirmed through path tracing using Figure 3.4.

The standardised variance and covariance between the traits is calculated using the same formula as before, where the total variance is the sum of the variance components ($V = A + C + E$), and the variance components are the result of the variance divided by the total variance (e.g. for genetic influences: ($h^2 = \frac{A}{V}$). For example, matrix V is:

$$V = A + C + E = \begin{bmatrix} a_{11}^2 + c_{11}^2 + e_{11}^2 & a_{21}a_{22} + c_{21}c_{22} + e_{21}e_{22} \\ a_{21}a_{22} + c_{21}c_{22} + e_{21}e_{22} & a_{21}^2a_{22}^2 + c_{21}^2c_{22}^2 + e_{21}^2e_{22}^2 \end{bmatrix}$$

$$= \begin{bmatrix} Var_{Tr1} & Cov_{(Tr1,Tr2)} \\ Cov_{(Tr1,Tr2)} & Var_{Tr2} \end{bmatrix}$$

and matrix h^2, for the standardised genetic variance is:

$$h^2 = \begin{bmatrix} \dfrac{a_{11}^2}{a_{11}^2 + c_{11}^2 + e_{11}^2} & \dfrac{a_{21}a_{22}}{a_{21}a_{22} + c_{21}c_{22} + e_{21}e_{22}} \\ \dfrac{a_{21}a_{22}}{a_{21}a_{22} + c_{21}c_{22} + e_{21}e_{22}} & \dfrac{a_{21}^2a_{22}^2}{a_{21}^2a_{22}^2 + c_{21}^2c_{22}^2 + e_{21}^2e_{22}^2} \end{bmatrix}$$

Next, we use the variance-covariance matrices to compute the phenotypic correlation and the genetic, shared and nonshared environmental influences. This is calculated using the same Cholesky formula to standardise the variance-covariance matrix in the univariate model (`solve(sqrt(I*V))`%&%V), where V is the standardised variance matrix. Because the correlated factors solution uses correlations, this is where the Cholesky decomposition is converted into a correlated factors model (worked example provided in Appendix 3.4).

A higher cross-twin cross-trait correlation for MZ twins than DZ twins ($rMZxTwxTr$ > $rDZxTwxTr$) indicates that additive genetic influences contribute to the covariance between the traits, and an MZ correlation more than twice the DZ correlation indicates non-additive genetic influences ($rMZxTwxTr$ > $2rDZxTwxTr$). An equal cross-twin cross-trait correlation across zygosity ($rMZxTwxTr$ = $rDZxTwxTr$) indicates shared environmental influences. A significant within-twin cross-trait ($Cov_{(Tr1,Tr2)}$) covariance but a nonsignificant cross-twin cross-trait covariance ($xTwxTr$) indicates nonshared environmental influences contribute to the covariance between the traits. The correlated factors model is shown in Figure 3.5, modelled separately for MZ and DZ twins by the genetic correlation of 1 or 0.5.

The expected variance-covariance matrix can be derived from this diagram by tracing the paths (Plomin et al., 2013).

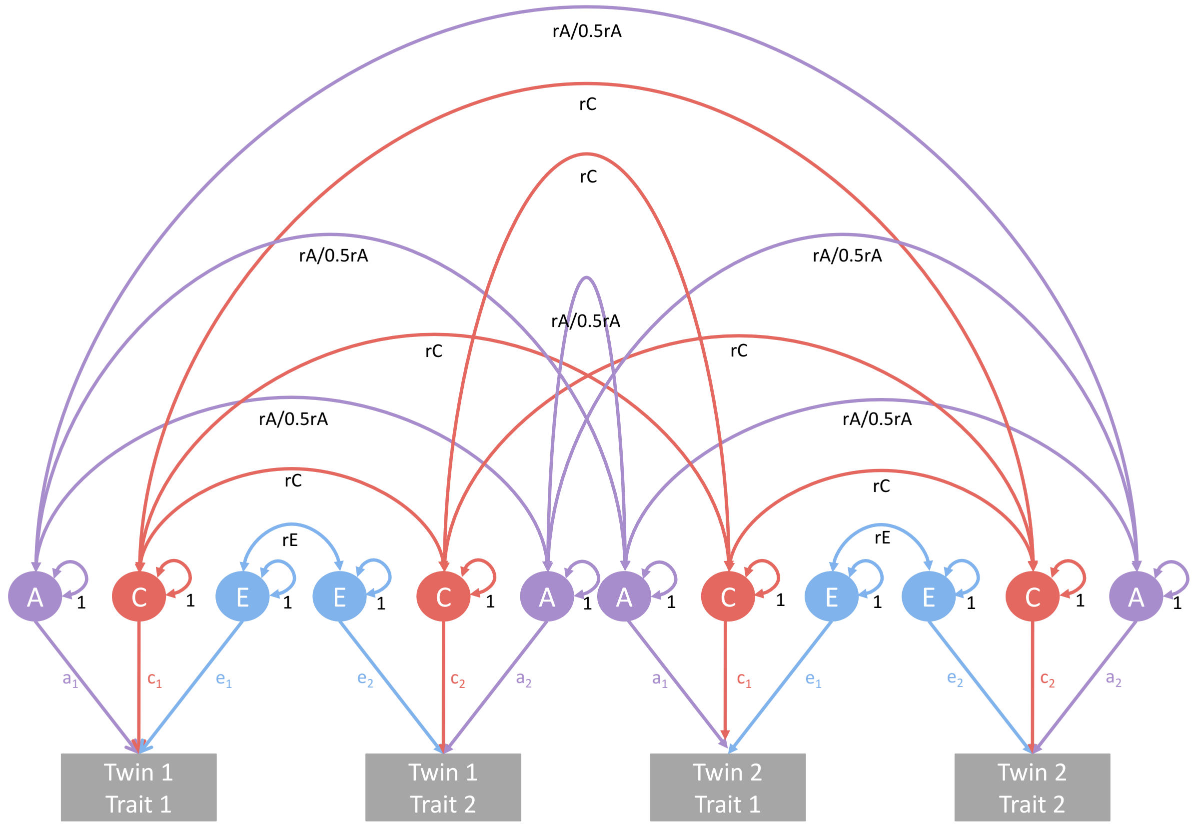


Figure 3.5 Path diagram for the bivariate correlated factors solution, showing both Twin 1 and Twin 2 paths. The variance in each trait is calculated by adding the legitimate paths to the trait (e.g. Trait 1= $\boldsymbol{a_1^2 + c_1^2 + e_1^2}$). The genetic (rA), shared (rC) and nonshared (rE) environmental correlations are calculated as the proportion of the A, C and E variance components that are shared between the traits. The proportion of the phenotypic correlation due to additive genetic, shared and nonshared environmental influences is calculated by following the legitimate paths from Twin 1 Trait 1 to Twin 1 Trait 2 (or Twin 2 Trait 1 to Twin 2 Trait 2): genetic ($\boldsymbol{rPH_A}$) = $\boldsymbol{a_1 \times rA \times a_2}$, shared environmental ($\boldsymbol{rPH_C}$) = $\boldsymbol{c_1 \times rC \times c_2}$, nonshared environmental ($\boldsymbol{rPH_E}$) = $\boldsymbol{e_1 \times rE \times e_2}$. We use OpenMx modelling to equate the variance across twin order. The cross twin cross trait covariance (xTwxTr) is calculated by combining the additive genetic and shared environmental covariance in Twin 1 Trait 1 and Twin 2 Trait 2, where the genetic covariance for MZ twins is correlated 1, and for DZ twins is correlated 0.5 ($\boldsymbol{MZ = a_1 \times 1 \times a_2 + c_1 \times 1 \times c_2, DZ =}$

$\boldsymbol{a_1 \times 0.5 \times a_2 + c_1 \times 1 \times c_2}$). The covariance between the twins for each trait ($\boldsymbol{Cov_{xTw\,Tr1}}$ and $\boldsymbol{Cov_{xTw\,Tr2}}$) is computed by the paths connecting Twin 1 Trait 1 to Twin 2 Trait 1 ($\boldsymbol{a_1 \times 1\ (or\ 0.5) \times a_1 + c_1 \times 1 \times c_1}$), and Twin 1 Trait 2 to Twin 2 Trait 2 ($\boldsymbol{a_2 \times 1\ (or\ 0.5) \times a_2 + c_2 \times 1 \times c_2}$).

3.2.1.5 Bivariate ACE model with continuous-ordinal variables

To estimate the A, C and E covariance components between trust and the other wellbeing measures, the bivariate model was extended to combine a threshold liability model. This is visualised in Figure 3.6, but it is not a path diagram therefore is not traceable. As before, we estimate the threshold for the liability instead of the mean of trust. The A, C and E variance components are then calculated in the same way as the bivariate model, and the A, C and E variance components for trust are estimated for the liability of trust. Finally, the additional code to decompose the variance for trust constrains the total variance to 1 using the same function as before (`mxConstraint()`).

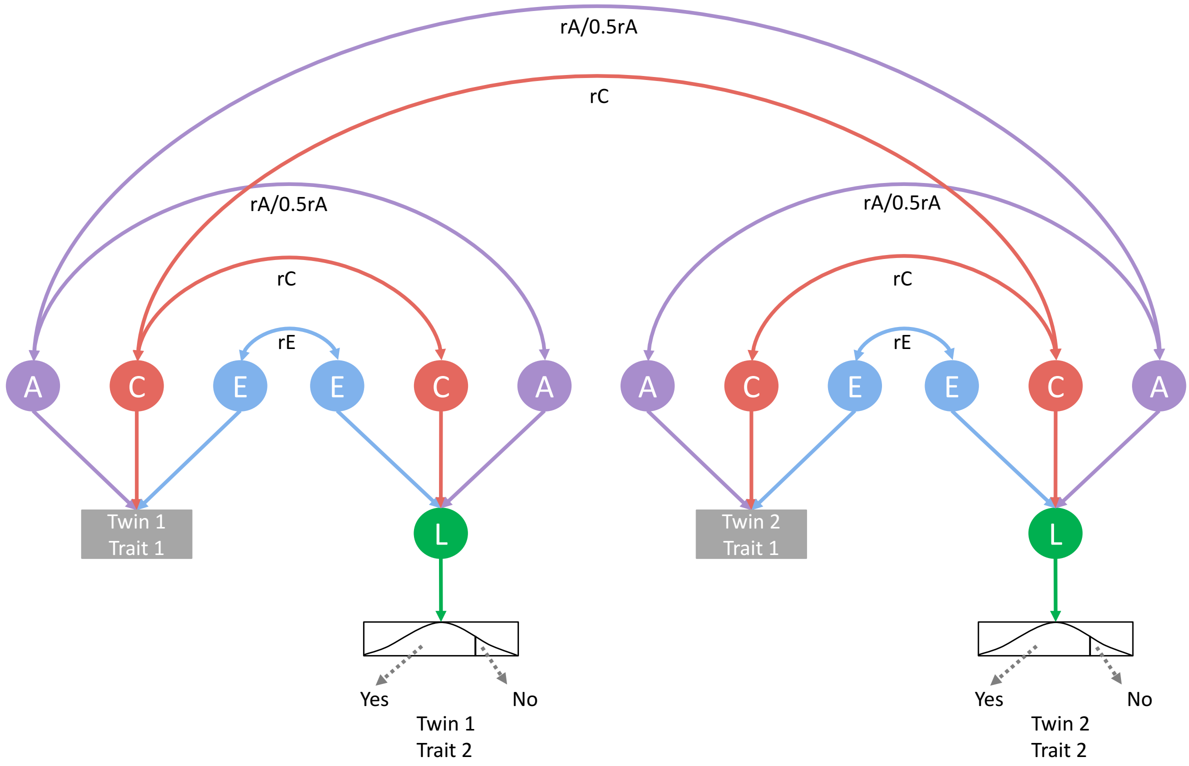


Figure 3.6 Visualisation of the bivariate model with one continuous and one ordinal variable. The A, C and E components of variance are calculated for the liability rather than the trait. The key difference between this model and the correlated factors model is the estimation of the A, C and E variance components for the threshold liability instead of the trait mean.

3.2.1.6 Summary of twin modelling in this thesis

In this thesis, I have used bivariate ACE modelling to estimate the genetic (A), shared environment (C) and nonshared environmental (E) influences on each of the wellbeing measures as well as the degree to which the A, C and E components of variance are shared between the wellbeing measures. I ran a series of bivariate models, using all possible combinations of pairs of the wellbeing indicators. I then ran a bivariate model for continuous and ordinal variables to compute estimates for trust, which has a dichotomous response scale. The results of this analysis are in Chapter 5.

3.3.2 *Principal Components Analysis (PCA)*

In this thesis, I have used Principal Components Analysis (PCA) to describe the variation in the 14 wellbeing indicators using a smaller number of components. In Chapter 4, this is applied to the phenotypic variation. In Chapter 5, this is applied to the variation in the genetic and the non-shared environmental influences. PCA provides an empirical summary of the data, which is simpler to visualise and interpret (Davis & Plomin, 2010). It is useful as a form of data reduction because it aims to account for all the variance in a dataset with a few components, unlike Factor Analysis which only explains the variance between variables (Wold, Esbensen, & Geladi, 1987).

PCA is based on the mathematical assumption that matrix X, with N rows (that represent i objects) and K columns (that represent k variables, which are assumed to correlate), can be explained by the product of two vectors T and P', plus matrix E of the residual variance:

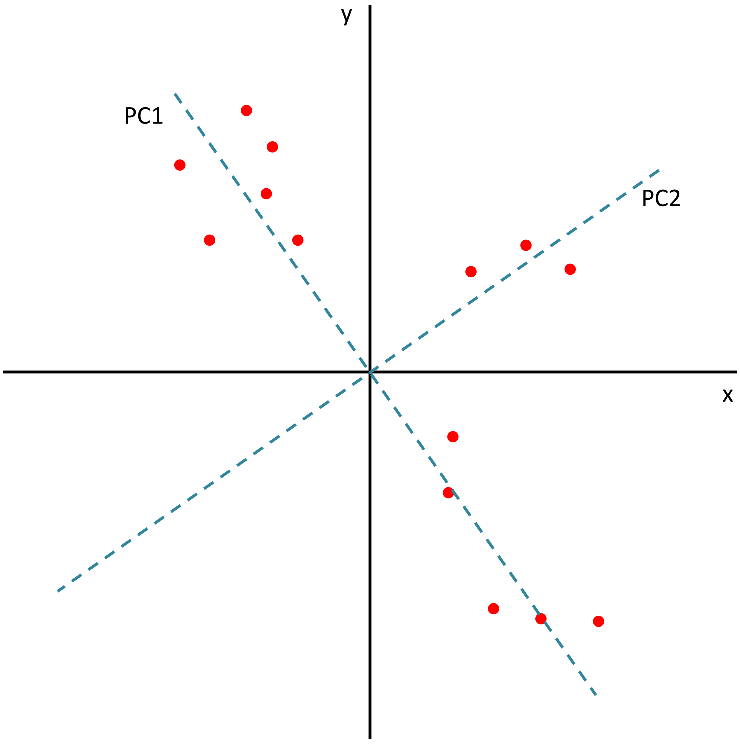
$$X = TP' + E$$

where the columns of matrix T provide a picture of the variance patterns of the objects in X, and the rows of P' provide a picture of the patterns in the variables (Wold, 1987). The product of TP' is the principal component. This equation represents a linear regression, and can be extended easily to include multiple components:

$$X = T_1P_1' + \cdots + T_aP_a' + E$$

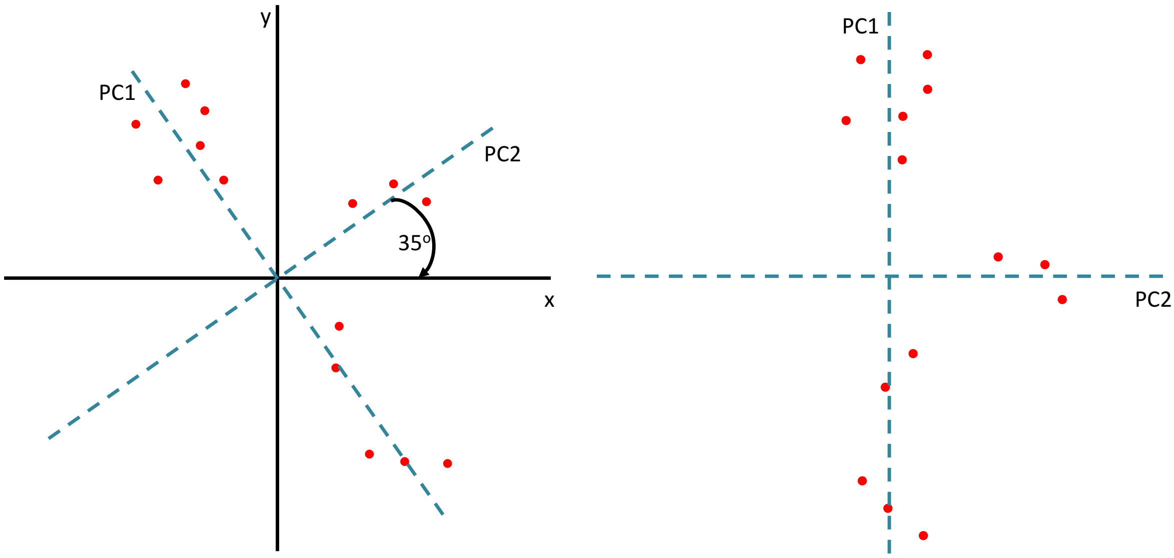
where the a number of components explain the maximum variance in X, but a is always smaller than the number of variables (k) in X (Wold et al., 1987).

To reduce the variance of the 14 wellbeing indicators into principal components, we start with a correlation matrix. In our analysis, we calculate the correlations between the variables using twin modelling in OpenMx, as described above. PCA then attempts to decompose the entire variance in the correlation matrix using eigenvalues and eigenvectors (Wold et al., 1987). Simply, this creates a number of vectors that are positioned in the 14-dimensional space (as there are 14 wellbeing indicators) to explain the most variance in the correlation matrix, until all of the matrix variance has been explained. New vectors are added in the 14-dimensional space orthogonal to the vectors already in the space. This can be visualised for two components as:



Generally, any vector with an eigenvalue greater than 1 explains more variance than one variable in the correlation matrix (Wold et al., 1987). This often determines the number of principal components included in a model, known as the Kaiser criterion (Costello & Osborne, 2005).

For a number of components, we obtain the loadings of each variable. This represents the correlation between the principal component and the variable (Abdi & Williams, 2010). The solution is often rotated to interpret the components more easily. Varimax rotation (Kaiser, 1958) is often used to simplify the interpretation so that each component represents a small number of variables (Abdi & Williams, 2010). This is achieved by finding the linear combination of the original variables that maximises the variance of the squared loadings (Abdi & Williams, 2010). Basically, the components are rotated so that they represent the axes of the dimensional space. Consequently, the component loadings of a variable represent its relative position in the dimensional space, because the components are axes. For example, Varimax rotation with two principal components above:



We can assess how well the components represent the variables by the communality, uniqueness and the complexity of the component loadings. The communality is calculated by the sum of squared component loadings for each variable, which indicate the degree of variance explained by the components. If the communalities are low, it suggests that the variable is dissimilar from the other variables, and that an additional component could be required (Costello & Osborne, 2005). The uniqueness of a variable indicates the degree to which the variable is distinct from the other variables, ranging from 0 for sharing all variance with the other variables, to 1 for sharing nothing. Initially, the communality is assumed to be 1 and uniqueness is assumed to be 0. This is because PCA assumes that the total variance in the correlation matrix can be completely explained by the components. However, because we want to explain the variance in the matrix with as few components as possible, the communality is often less than one and the uniqueness will be greater than 0. Hofmann's (1978) index of complexity indicates the average number of principal components required to account for a variable. In a perfect solution, the complexity of each variable would be one, suggesting that one principal component accounts for each variable (Pettersson & Turkheimer, 2010). However, in reality it is unlikely that each variable will be accounted for by one component, so we would expect the complexity to be greater than 1.

3.3.2.1 Methodological PCA decisions: rotation, component extraction and cut-off loadings

I used PCA because it accounts for all of the variance in the correlation matrix, rather than only the variance shared between the variables as in factor analysis (Abdi & Williams, 2010). We are trying to answer a specific question of data reduction, with the aim of visualising the similarities between the variables and distinguishing differences. PCA is quite subjective in that many decisions are required from the researcher. However, when making decisions often the data will be modelled similarly when there are many variables and observations (Revelle, 2009). In this thesis, I explicitly made decisions on the rotation method, component extraction and the cut-off for the loadings, as discussed below.

Rotation

I chose to use Varimax rotation (Kaiser, 1958), which is the most common orthogonal rotation method (Costello & Osborne, 2005). Components remain orthogonal, useful for visualisation as the axes of the plot will be the components (as demonstrated above). I used Varimax rotation to aid my interpretation of the relationship between the variables.

Component extraction

It is difficult to determine the number of components to best explain the variability in a dataset, with a trade-off between an adequate number of components and parsimony. To decide on the number of components for the wellbeing indicators, I used the eigenvalues, the scree test (Cattell, 1966), parallel analysis (Horn, 1965), very simple structure (VSS; Revelle & Rocklin, 1979) and Velicer's minimum average partial correlation test (MAP; 1976).

As mentioned before, components with eigenvalues greater than 1 explain more variance than one variable, which I believe is a minimum requirement for a component. The scree test assesses the scree plot to determine the 'elbow' of the plot, at which point there is a drop in the eigenvalues, and the number of eigenvalues before the change in gradient determines the number of components. Parallel analysis formally tests whether the solutions are due to chance (Wood, Akloubou Gnonhosou, & Bowling, 2015). It recommends the number of components with eigenvalues greater than eigenvalues of components for a random dataset of the same size (Horn, 1965). VSS compares the solution to a simple structure where all but the largest loadings on each component are set to zero, and tends to reach a maximum at the most optimal number of components (Revelle & Rocklin, 1979).

MAP is performed on the correlation matrix and identifies components that account for systematic variance.

The different methods to determine the number of components do not always conform. MAP and parallel analysis are formal statistical methods and arguably provide a stronger basis for recommendation (Wood et al., 2015). I interpreted the components with eigenvalues greater than one as the maximum number of components, then looked for agreement between the other methods to determine the optimal number of components. I also assessed the component loadings, the communalities and the complexity of the variables. I aimed to explain the most variance in the data with the minimum number of components, with little variable complexity.

Loading cut-offs

In PCA, the loadings of a variable onto a component indicate the correlation between the variable and the component. A higher loading indicates that the component explains a greater amount of the variance in the variable. Cut-off values for loadings are relatively arbitrary, because unless there is a zero loading, the component has captured some of the variance in the variable. However, I chose a cut-off value of 0.45, which explains approximately 20% (0.45^2x100) of the variance in the variable (Comrey & Lee, 2013). This seems appropriate considering Varimax maximises large loadings and reduces small loadings (Abdi & Williams, 2010).

It is worth noting that PCA provides one method to represent the complex relationship between the diverse indicators of wellbeing. Often, PCA does not provide a perfect fit, and much of the complexity may be lost. We need to ensure we consider the degree of variance explained by the PCA to assess whether it represents the data well.

3.4 Statistical procedures in this thesis

These methods and procedures are used in the following empirical chapters: PCA (Chapter 4 and 5), univariate twin modelling (Chapter 5), bivariate twin modelling (Chapter 5). Chapter 6 uses MZ differences analyses. Chapter 7 uses a different method of multiple linear regression applied to multiple large datasets. Further details of how these specific methods were applied are provided within each chapter.

3.5 Chapter summary

This chapter described TEDS, the main sample used in this thesis, with a specific focus on the wellbeing data collected during adolescence. This chapter also outlined the principles of twin modelling, including the basic univariate model and extensions to this basic model, and principal components analysis. Each empirical chapter will describe specific methods in more detail. The first two empirical chapters (Chapters 4 and 5) will use twin methods and PCA to explore the phenotypic, genetic and environmental similarities in the variation of the wellbeing indicators.

Chapter 4. The phenotypic relationship between subjective and eudaimonic wellbeing indicators in adolescence

4.1 Chapter overview

In Chapter 3, I outlined the basic principles of principal components analysis (PCA). In this chapter, I apply PCA to explore the phenotypic relatedness of subjective and eudaimonic wellbeing indicators. Previous research has suggested a bi-factor structure to wellbeing (Longo, Coyne, & Joseph, 2017; Lui & Fernando, 2018), yet little empirical research has explored the phenotypic structure of wellbeing using a diverse range of eudaimonic wellbeing indicators. Furthermore, given the inconsistency in the positive traits considered as components of eudaimonic wellbeing (see Chapter 1), research is needed that explores a diverse range of traits within the same sample. I characterised the relationship between 14 subjective and eudaimonic wellbeing indicators using data from over 10,000 individuals from the Twins Early Development Study (TEDS). I also explored how these indicators related to important life outcomes including relationship quality, personality, school engagement and behavioural problems.

In this chapter I aim to:

1. Understand how diverse indicators of subjective and eudaimonic wellbeing are related in adolescence
2. Explore differences in the associations between these wellbeing indicators and important life outcomes

4.2 Introduction

4.2.1 The structure of wellbeing

Subjective and eudaimonic wellbeing are distinct theories of wellbeing, yet are highly correlated in empirical research (Disabato, Goodman, Kashdan, Short, & Jarden, 2016; Keyes, 2002; Linley, Maltby, Wood, Osborne, & Hurling, 2009). Studies that have explored the structure of wellbeing have mostly supported a bi-factor model, with one general wellbeing factor that explains most variance, and subsequent factors that represent the components of subjective and eudaimonic wellbeing (Chen, Jing, Hayes, & Lee, 2013; De Bruin & Du Plessis, 2015; Jovanović, 2015). Each component captures aspects of wellbeing above and beyond overall wellbeing (De Bruin & Du Plessis, 2015), providing evidence that wellbeing is an overarching construct for subjective and eudaimonic wellbeing.

However, the number of components included to represent subjective and eudaimonic wellbeing is not consistent. There are three main models of the structure of wellbeing: one subjective component and one eudaimonic component (Diener et al., 2010; Henderson & Knight, 2012; Waterman, 2008); one component of subjective wellbeing and multiple components of eudaimonic wellbeing (De Bruin & Du Plessis, 2015; Jovanović, 2015; Su, Tay, & Diener, 2014); and multiple subjective components and multiple eudaimonic components (Huppert & So, 2013; Keyes, 2002). This lack of consistency is mainly caused by the absence of clarity on what traits constitute eudaimonic wellbeing, and whether eudaimonic traits should be represented as a single component of eudaimonic wellbeing or as multiple eudaimonic components. Though it is likely subjective wellbeing and eudaimonic wellbeing are components of a shared overarching construct, we need research that captures a diverse range of eudaimonic traits to understand the relationship between subjective and eudaimonic wellbeing and to identify the traits that can be considered as wellbeing indicators.

There is also little agreement on which, or how many, positive traits should be included to assess wellbeing. This is emphasised in my review in Chapter 1, where I identified 38 different traits that were used to capture eudaimonic wellbeing across 20 instruments, with each instrument measuring between two (e.g. Keyes, 2009) to 17 (Su et al., 2014) traits (see section 1.2.1 and Appendix 1.2). As the prevalence of wellbeing differs depending on how wellbeing is defined and measured (Hone, Jarden, Schofield, & Duncan, 2014), it is incredibly important to understand what traits should be used to represent subjective and eudaimonic wellbeing. Research needs to explore the structure of wellbeing by assessing the relationship between a diverse range of subjective and eudaimonic wellbeing indicators to truly understand the complexity of wellbeing.

4.2.2 Adolescent wellbeing and important life outcomes

Exploring how a range of subjective and eudaimonic wellbeing indicators are related to important life outcomes is a crucial analysis that could help to characterise the underlying complexity of the experience of wellbeing. Previous work has shown that in adolescence, subjective wellbeing is associated with peer and parental relationships (Oberle, Schonert-Reichl, & Zumbo, 2011; Wang, Davis, Wootton, Mottershaw, & Haworth, 2017), school engagement (Lewis, Huebner, Malone, & Valois, 2011), and behaviour (Park, 2004). Furthermore, personality has been associated with subjective wellbeing across ages (Anglim

& Grant, 2014) but less is known about the correlates of eudaimonic wellbeing during adolescence. We aim to explore whether the relationships with subjective wellbeing are seen across diverse indicators of eudaimonic wellbeing and whether there is specificity in the links between the different components of wellbeing and life outcomes.

4.2.3 The current study

This is the first study to attempt to understand the experience of wellbeing using such a wide range of wellbeing indicators. Using data collected on 14 subjective and eudaimonic wellbeing indicators in adolescence, our primary aim is to understand how diverse components of wellbeing are related. We test the structure of wellbeing using multiple subjective components and multiple eudaimonic components, as in previous research (Huppert & So, 2013; Keyes, 2002). Secondly, we aim to understand how wellbeing, measured using as both subjective and eudaimonic indicators, is related to outcomes that are consistently associated with subjective wellbeing, including the quality of relationships, personality, school engagement, and behavioural strengths and difficulties.

4.3 Method

4.3.1 Sample and measures

Data was collected as part of the Twins Early Development Study (TEDS), as described in Chapter 3. A critical aim of this study was to collect data on a wide range of positive psychological measures on a large and representative sample. Here, we used a total of 14 scales as wellbeing indicators (for a detailed description, see Chapter 3), resulting in an internationally unique dataset on adolescent wellbeing. We included nine measures from the web data collection (life satisfaction, subjective happiness, optimism, gratitude, hopefulness, grit, ambition, curiosity, and subjective health), and seven measures from the booklet (life satisfaction, subjective happiness, autonomy, competence, relatedness, meaning in life, and trust). Measures of life satisfaction and subjective happiness were included in both data collection methods; when participants had responses for both, the mean score was taken. We measured subjective wellbeing using life satisfaction and subjective happiness and measured eudaimonic wellbeing using twelve diverse indicators: autonomy, competence, relatedness, meaning in life, trust, optimism, gratitude, hopefulness, grit, ambition, curiosity, and subjective health.

4.3.1.1 Related measures

The related measures were used to assess important life outcomes. These included relationships, personality, school engagement, and behavioural strengths and difficulties (Table 4.1). Relationships, personality and school engagement were collected on the web, and the behavioural strengths and difficulties were in the booklet. Six of the measures had low internal reliability (< 0.70: parental control, openness, agreeableness, peer problems, conduct problems, prosocial behaviour), which suggests these measures do not have good internal consistency. This should be considered when interpreting the results.

4.3.2 Data Analyses

First, we made composites using the mean of the items, requiring at least 50% non-missing items per measure. Analyses consisted of three parts: creating a correlation matrix for the wellbeing indicators; assessing the relationship between the wellbeing indicators by

Table 4.1 Description of related measures.

Measure	Scale	Reference	Chronbach's Alpha (α)	Number of items; (number of reversed items)	Response scale
(a) Relationships					
Peer attachment	Peer attachment subscale of the inventory of parent and peer attachment	Armsden & Greenberg (1987)	0.93	25 (7)	Five-points: 'almost never or never true' to 'almost always or always true'
Parental control	Items from the NICHD early childcare and youth development study	NICHD (2005); Brody et al. (1994)	0.66	8 (8)	Four-points: 'my parent(s) decide' to 'I decide all by myself'
Parental monitoring	Parental monitoring scale	NICHD (2005); Maume (2013)	0.86	6	Four-points: 'doesn't know' to 'knows everything'
(b) Personality					
Neuroticism	Five-factor model rating form of personality	Mullins-Sweatt, Jamerson, Samuel, Olson, & Widiger, (2006)	0.70	6	Five-points from 'high' to 'low' for different descriptive words of personality traits
Extraversion	Five-factor model rating form of personality	Mullins-Sweatt, Jamerson, Samuel, Olson, & Widiger, (2006)	0.70	6	Five-points from 'high' to 'low' for different descriptive words of personality traits

Measure	Scale	Reference	Chronbach's Alpha (α)	Number of items; (number of reversed items)	Response scale
Openness	Five-factor model rating form of personality	Mullins-Sweatt, Jamerson, Samuel, Olson, & Widiger, (2006)	0.62	6	Five-points from 'high' to 'low' for different descriptive words of personality traits
Agreeableness	Five-factor model rating form of personality	Mullins-Sweatt, Jamerson, Samuel, Olson, & Widiger, (2006)	0.67	6	Five-points from 'high' to 'low' for different descriptive words of personality traits
Conscientiousness	Five-factor model rating form of personality	Mullins-Sweatt, Jamerson, Samuel, Olson, & Widiger, (2006)	0.77	6	Five-points from 'high' to 'low' for different descriptive words of personality traits
(c) School Engagement					
Teacher-Student Relations	School Engagement Instrument[a]	Appleton, Christenson, Kim, & Reschly (2006)	0.91	6	Four-points: 'strongly disagree' to 'strongly agree'
Control/relevance of schoolwork	School Engagement Instrument	Appleton, Christenson, Kim, & Reschly (2006)	0.76	4	Four-points: 'strongly disagree' to 'strongly agree'
Peer support for learning	School Engagement Instrument	Appleton, Christenson, Kim, & Reschly (2006)	0.89	3	Four-points: 'strongly disagree' to 'strongly agree'

Measure	Scale	Reference	Chronbach's Alpha (α)	Number of items; (number of reversed items)	Response scale
Future aspirations and goals	School Engagement Instrument	Appleton, Christenson, Kim, & Reschly (2006)	0.92	3	Four-points: 'strongly disagree' to 'strongly agree'
Family support for learning	School Engagement Instrument	Appleton, Christenson, Kim, & Reschly (2006)	0.95	3	Four-points: 'strongly disagree' to 'strongly agree'
(d) Strengths and Difficulties Questionnaire					
Anxiety/ emotional problems	Strengths and difficulties questionnaire (SDQ)[b]	Goodman (1997)	0.69	5	Three-points: 'Not true' to 'very true'
Peer relationship problems	SDQ	Goodman (1997)	0.55	5 (2)	Three-points: 'Not true' to 'very true'
Hyperactivity/ inattention	SDQ	Goodman (1997)	0.73	5 (2)	Three-points: 'Not true' to 'very true'
Conduct problems	SDQ	Goodman (1997)	0.54	5 (1)	Three-points: 'Not true' to 'very true'
Total behavioural difficulties	SDQ	Goodman (1997)	0.78	20 (5)	Three-points: 'Not true' to 'very true'
Prosocial behaviour	SDQ	Goodman (1997)	0.69	5	Three-points: 'Not true' to 'very true'

Note. Relationships, personality and school engagement were collected on the web. Strengths and difficulties were collected on the booklet.

[a] Reduced to 19 items after the initial pilot study due to space constraints.

[b] The SDQ item 'I am often unhappy, down-hearted or tearful' omitted and replaced in analysis with 'I felt miserable or unhappy' from the Moods and Feelings Questionnaire (Angold et al., 1995) due to their similarity.

performing principal components analysis (PCA); and assessing the relationship between the wellbeing indicators and life outcomes.

All correlations were calculated using OpenMx (Neale et al., 2015) so that full-information maximum likelihood estimation twin-modelling made use of all data and we could account for the age, sex and relatedness of participants. Correlations between trust and the other measures were tetrachoric. We checked that each measure correlated at least ±0.30 with another positive measure to ensure that the use of principal component analysis was acceptable (Tabachnick & Fidell, 2013).

We then performed PCA with varimax rotation to reduce the complex relationship among the wellbeing indicators to a small number of spatial components. As described in Chapter 3, the number of components to extract was decided by: the number of eigenvalues less than one; the elbow of the scree plot; parallel analysis (Horn, 1965); and Velicer's minimum average partial correlation test (Velicer, 1976). We considered measures to load onto a component if the loading was at least 0.45, which indicates that the component explains at least 20% of the variance in the measure. Measures were considered complex with loadings higher than 0.45 on more than one component, or loadings with a difference of less than 0.20 across components. After determining the number of components, we presented the loadings visually by plotting each component as an axis on a graph.

Finally, we assessed the differences in the correlations between the components that emerged and the related outcomes encompassing relationships, personality, school engagement and behavioural strengths and difficulties. We also assessed the relationship between the 14 wellbeing indicators and the related outcomes.

4.4 Results and discussion

4.4.1 The relationship between the positive measures

Table 4.2 shows the correlation matrix for the 14 wellbeing indicators (range = 0.09 to 0.64). Our components of subjective wellbeing (subjective happiness and life satisfaction) were correlated 0.63, indicating that they are related but distinct traits. Though some of the correlations between the components of subjective wellbeing and the eudaimonic traits are similar (e.g. with optimism and curiosity), there is also some specificity in the correlations such as with relatedness (life satisfaction = 0.64; subjective happiness = 0.55). This emphasises the value of measuring the components of subjective wellbeing distinctly.

Across the wellbeing indicators, the strongest correlations are between our subjective wellbeing indicators and the basic psychological needs (competence, relatedness and autonomy), which range 0.50 to 0.64. This may reflect the importance of fulfilling psychological needs in order to experience a sense of subjective wellbeing (Deci & Ryan, 2000). Generally, life satisfaction has the strongest correlations with the other measures (mean = 0.50), which is expected, as the life satisfaction measure requires individuals to reflect on their life as a whole. This could indicate that life satisfaction, as a component of subjective wellbeing, incorporates aspects of eudaimonic wellbeing and is a useful indicator of overall wellbeing. However, life satisfaction only has moderate phenotypic correlations with our other wellbeing indicators, suggesting that it cannot capture all aspects of overall wellbeing. This supports previous studies that have found valuable information will be lost If wellbeing is only measured by life satisfaction (Huppert & So, 2013). Nevertheless, in research where space or time constraints limit the number of measures that can be included, life satisfaction may be the best single indicator of overall wellbeing.

Trust and curiosity have the weakest correlation (0.09), which indicates they are not related eudaimonic traits. Curiosity and subjective health show the overall weakest correlations with the rest of the measures (mean 0.24 and 0.26 respectively), suggesting they are phenotypically distinct. Trust also shows generally weaker correlations compared to the other measures but has moderate correlations with life satisfaction and relatedness (both 0.44). It is possible that the positive traits that show weaker correlations are correlates of wellbeing rather than distinct eudaimonic traits.

The average phenotypic correlation between the booklet measures (relatedness, autonomy, competence, meaning and trust) was moderate (0.50), whereas the average correlation between the web measures (optimism, gratitude, hopefulness, grit, ambition, curiosity and subjective health) was modest (0.34). We would expect the higher average correlations on the booklet because three of the five measures are subscales that together measure the basic psychological needs. The average correlation across the web and the booklet measures was 0.31, which reflects the correlation between the web measures. This suggests that the correlations are similar across data collection methods as they are within the same data collection method. However, it is difficult to draw strong conclusions because the specific wellbeing indicators differ across data collection.

Table 4.2. Correlations (95% confidence intervals) and number of complete twin pairs for the 14 wellbeing indicators.

	Happ.	Rel.	Aut.	Comp.	Grat.	Opt.	Mean.	Trust	Hope.	Amb.	Grit	Cur.	Health
Life Satisfaction	0.63 (0.62, 0.65)	0.64 (0.62, 0.65)	0.59 (0.57, 0.60)	0.58 (0.57, 0.60)	0.59 (0.57, 0.60)	0.50 (0.48, 0.52)	0.59 (0.57, 0.60)	0.44 (0.41, 0.46)	0.59 (0.57, 0.60)	0.34 (0.31, 0.37)	0.36 (0.33, 0.38)	0.23 (0.20, 0.26)	0.40 (0.37, 0.42)
Subjective Happiness		0.55 (0.53, 0.57)	0.50 (0.48, 0.52)	0.51 (0.49, 0.53)	0.48 (0.46, 0.50)	0.47 (0.45, 0.49)	0.54 (0.52, 0.55)	0.38 (0.35, 0.41)	0.49 (0.47, 0.51)	0.24 (0.22, 0.27)	0.24 (0.22, 0.27)	0.21 (0.19, 0.24)	0.33 (0.30, 0.35)
Relatedness (b)			0.64 (0.64, 0.64)	0.59 (0.59, 0.60)	0.42 (0.39, 0.45)	0.38 (0.34, 0.41)	0.50 (0.48, 0.51)	0.44 (0.41, 0.47)	0.37 (0.33, 0.40)	0.26 (0.22, 0.30)	0.28 (0.24, 0.32)	0.14 (0.10, 0.18)	0.28 (0.24, 0.29)
Autonomy (b)				0.63 (0.62, 0.63)	0.35 (0.31, 0.38)	0.38 (0.34, 0.41)	0.49 (0.47, 0.51)	0.39 (0.36, 0.42)	0.38 (0.35, 0.41)	0.22 (0.18, 0.26)	0.28 (0.24, 0.32)	0.12 (0.08, 0.17)	0.22 (0.18, 0.26)
Competence (b)					0.38 (0.35, 0.41)	0.45 (0.41, 0.48)	0.62 (0.61, 0.63)	0.38 (0.35, 0.41)	0.47 (0.44, 0.50)	0.37 (0.33, 0.40)	0.41 (0.37, 0.44)	0.25 (0.21, 0.28)	0.28 (0.25, 0.32)
Gratitude (w)						0.37 (0.35, 0.40)	0.39 (0.36, 0.43)	0.26 (0.23, 0.31)	0.49 (0.47, 0.51)	0.35 (0.32, 0.38)	0.31 (0.28, 0.33)	0.29 (0.27, 0.32)	0.29 (0.26, 0.31)
Optimism (w)							0.42 (0.38, 0.45)	0.39 (0.34, 0.44)	0.45 (0.43, 0.47)	0.35 (0.32, 0.37)	0.36 (0.33, 0.38)	0.20 (0.17, 0.22)	0.28 (0.25, 0.31)

Note: Rel. = Relatedness; Aut. = Autonomy; Comp. = Competence; Happ. = Subjective Happiness, Mean. = Meaning in Life; Grat. = Gratitude; Opt. = Optimism; Hope. = Hopefulness; Amb. = Ambition; Cur. = Curiosity, Health = Subjective Health. Colour of cell indicates strength of correlation, with white no correlation and red a correlation of 1.

Table 4.2. (Continued) Correlations (95% confidence intervals) and number of complete twin pairs for the 14 wellbeing indicators.

	Trust	Hopefulness	Ambition	Grit	Curiosity	Health (w)
Meaning in life (b)	0.36 (0.33, 0.39)	0.49 (0.46, 0.52)	0.42 (0.38, 0.45)	0.34 (0.30, 0.37)	0.30 (0.26, 0.33)	0.27 (0.23, 0.31)
Trust (b)		0.23 (0.19, 0.29)	0.16 (0.10, 0.22)	0.24 (0.18, 0.26)	0.09 (0.03, 0.16)	0.18 (0.13, 0.24)
Hopefulness (w)			0.50 (0.47, 0.52)	0.40 (0.37, 0.42)	0.46 (0.44, 0.47)	0.35 (0.33, 0.38)
Ambition (w)				0.45 (0.42, 0.47)	0.46 (0.44, 0.49)	0.21 (0.18, 0.24)
Grit (w)					0.21 (0.18, 0.24)	0.22 (0.19, 0.23)
Curiosity (w)						0.12 (0.09, 0.15)

Note: Opt. = Optimism; Hope. = Hopefulness; Amb. = Ambition; Cur. = Curiosity, Health = Subjective Health. Colour of cell indicates strength of correlation, with white no correlation and red a correlation of 1.

4.4.1.1 PCA: two-component solution

We extracted two PCA components based on agreement across the eigenvalues, scree plot, parallel analysis and Velicer's minimum average partial correlation test. Table 4.3 shows that each measure, apart from subjective health, loaded onto one of the components above 0.45. Gratitude, subjective health and optimism were complex, with similar loadings on both components (defined as a difference of <0.20). Taken together, the components explained 54% of the variance across the wellbeing indicators.

Table 4.3. Component loadings and proportion of variance explained for the 14 wellbeing indicators

	Component One	**Component Two**
Life Satisfaction	**0.78**	0.35
Subjective Happiness	**0.73**	0.25
Relatedness (b)	**0.81**	0.11
Autonomy (b)	**0.79**	0.09
Competence (b)	**0.72**	0.33
Gratitude (w)	**0.47**	**0.47**
Optimism (w)	**0.54**	0.37
Meaning in life (b)	**0.62**	0.42
Trust (b)	**0.64**	0.02
Hopefulness (w)	0.40	**0.70**
Ambition (w)	0.13	**0.80**
Grit (w)	0.28	**0.55**
Curiosity (w)	-0.02	**0.76**
Subjective Health (w)	0.37	0.28
Proportion of variance explained	0.33	0.21

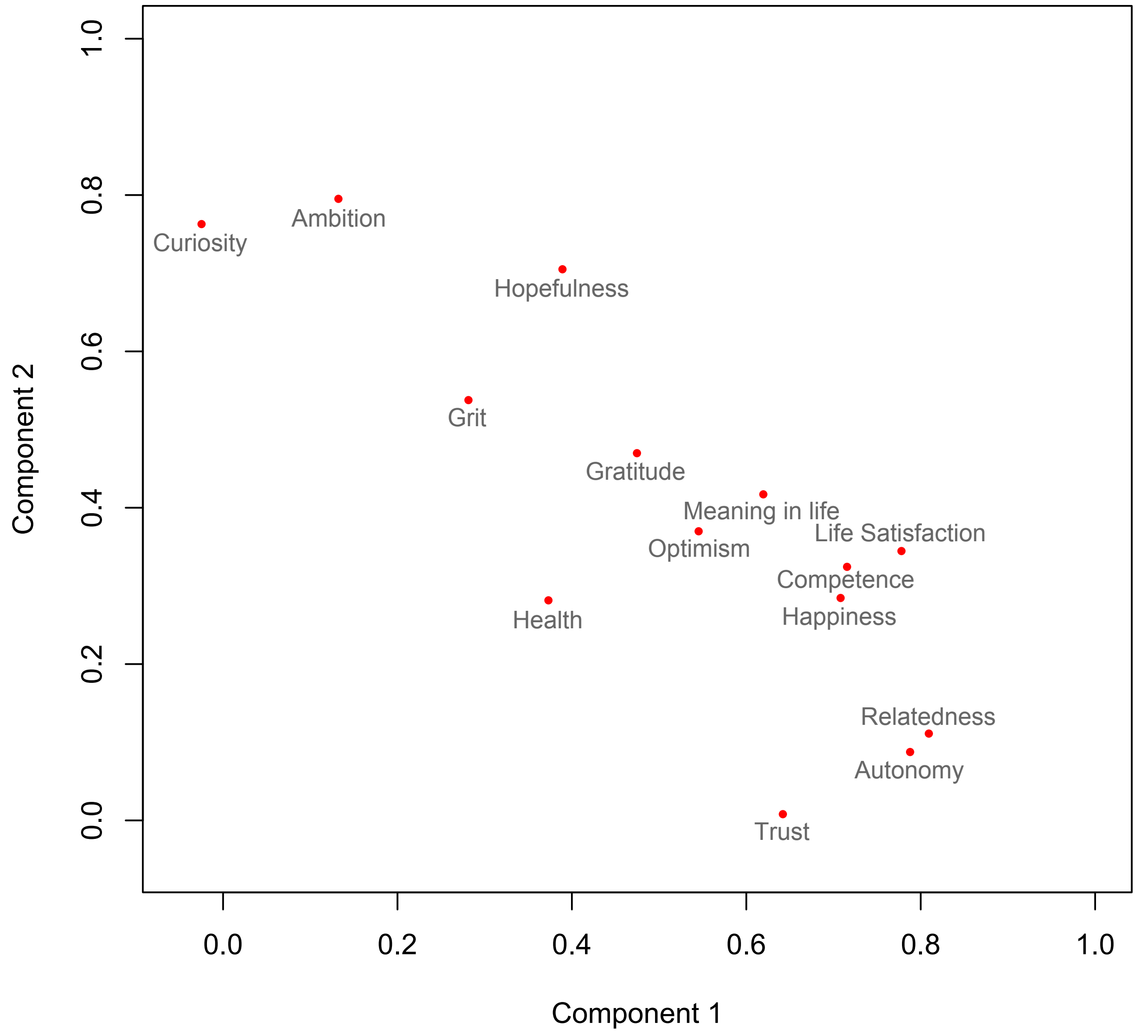


Figure 4.1. The relationship between 14 positive psychological measures, with principal components as axes. The relative positioning of the measures represents their phenotypic similarity. Similar measures are closer together, and dissimilar measures further apart.

Figure 4.1 represents the relationship between the positive measures, with each axis one component from the PCA. The relative positioning of the measures indicates their phenotypic similarity in relation to our components of wellbeing. This figure emphasises the similarity between life satisfaction, competence, subjective happiness, meaning in life, optimism and gratitude, and between relatedness and autonomy. It also emphasises the lower phenotypic overlap in curiosity, ambition, hopefulness and grit in comparison to the other wellbeing indicators.

After considering the factor loadings and the relative positioning of the measures, we concluded that the two PCA components are distinct. The first component represents aspects of subjective and eudaimonic wellbeing needed to thrive. Component One is defined mainly by subjective happiness, life satisfaction, relatedness, autonomy and competence, followed by lower (but still strong) loadings from trust, meaning in life, gratitude and optimism. Consequently, this component could be termed *flourishing* and represents an aspect of wellbeing with multiple subjective and multiple eudaimonic traits (Huppert & So, 2013; Keyes, 2002).

The traits that load onto our *flourishing* component are similar to the traits usually represented in instruments that measure subjective and eudaimonic wellbeing (Butler & Kern, 2016; Kern, Benson, Steinberg, & Steinberg, 2016; Keyes, 2009; Longo et al., 2017; Su et al., 2014; Tennant et al., 2007). For example, the five elements of PERMA (Butler & Kern, 2016; Seligman, 2012) are represented: positive emotion is represented through subjective happiness; engagement through autonomy; relationships through relatedness; meaning through meaning in life; and accomplishment through competence and life satisfaction. However, our component also includes more diverse eudaimonic traits such as optimism, trust and gratitude that are rarely or never included in wellbeing instruments, despite evidence that they are eudaimonic traits (e.g. Wood, Joseph, & Linley, 2007). This emphasises the difficulty of capturing all aspects of wellbeing within a single measure. It may be useful for research to use readily available validated scales that measure individual eudaimonic traits instead of attempting to create one instrument of wellbeing that captures all components.

The second component in our PCA is defined mostly by ambition, followed by curiosity, hopefulness, grit and gratitude – though meaning in life approaches an acceptable loading. The measures loading onto Component Two encompass positive thinking and appear to represent cognitive aspects of eudaimonic wellbeing. Consequently, this component was termed *aspirational drive*. This component of wellbeing may encompass the qualities that are associated with fulfilling ones potential, a key aspect of eudaimonic wellbeing (Waterman, 2010) and leads an individual to seek opportunities to develop skills and abilities.

The emergence of these components supports the two component structure of wellbeing suggested by previous literature (Chen et al., 2013; De Bruin & Du Plessis, 2015) but the components may not follow the theoretically distinct concepts of subjective and eudaimonic wellbeing. This supports the findings of Huppert and So (2013), where their exploratory factor analysis of subjective and eudaimonic wellbeing revealed a first *positive characteristic* factor that consisted of subjective and eudaimonic traits (emotional stability, vitality, resilience, optimism, happiness and self-esteem) and a second *positive functioning* factor consisting of only eudaimonic traits (engagement, meaning, positive relationships, and competence). Though we used different measures, we found similar relationships, where our first component represents subjective and eudaimonic wellbeing and our second component represents eudaimonic traits associated with cognitive functioning.

As these components appear to represent wellbeing clearly, we decided to report the subsequent analyses in this chapter using these components as well as the 14 indicators. The *flourishing* component of wellbeing was derived by creating a mean score of life satisfaction, subjective happiness, relatedness, autonomy, competence, trust, meaning in life, gratitude and optimism. The *aspirational drive* component of wellbeing was derived by creating a mean score of gratitude, hopefulness, ambition, curiosity and grit. A participant was required to have data for at least 50% of the traits to be included in the analysis.

4.4.2 Correlations with related measures: the two components

The correlations, calculated in OpenMx to adjust for zygosity, age and sex, in Table 4.4 show that, as expected, both components of wellbeing are associated with relationship quality, personality, school engagement and behavioural issues. We found that the *flourishing* component was more strongly associated with peer attachment, neuroticism and the behavioural strengths and difficulties. In contrast, the *aspirational drive* component was more strongly associated with openness and conscientiousness. This shows that the different components of wellbeing may have unique antecedents and outcomes and emphasises the need to measure wellbeing using diverse indicators that are free from the theoretical distinction of subjective and eudaimonic wellbeing.

Table 4.4 Correlations (95% confidence intervals) and number of complete twin pairs between the two components and the related measures involving relationships (a), personality (b), the five subscales of school engagement (c), and the five subscales of the strengths and difficulties questionnaire (d).

	Flourishing	***Aspirational drive***
(a) Relationships		
Peer attachment	0.52 (0.49, 0.54) 1015	0.35 (0.33, 0.38) 2059
Parental control	-0.03 (-0.06, 0.01) 1046	-0.04 (-0.07, -0.01) 2117
Parental monitoring	0.31 (0.28, 0.35) 1036	0.28 (0.25, 0.31) 2102
(b) Personality		
Neuroticism	-0.53 (-0.55, -0.50) 1014	-0.37 (-0.40, -0.35) 2034
Extraversion	0.43 (0.39, 0.46) 1012	0.41 (0.39, 0.43) 2031
Openness	0.06 (0.02, 0.10) 1010	0.17 (0.14, 0.20) 2027
Agreeableness	0.20 (0.16, 0.23) 1009	0.20 (0.17, 0.23) 2020
Conscientiousness	0.28 (0.25, 0.32) 1008	0.52 (0.50, 0.54) 2017
(c) School engagement		
Teacher-Student Relationship	0.18 (0.15, 0.22) 1084	0.20 (0.17, 0.22) 2225
Sense of control and relevance of schoolwork	0.22 (0.19, 0.26) 1083	0.29 (0.26, 0.31) 2222
Peer support for learning	0.28 (0.24, 0.31) 1080	0.23 (0.20, 0.25) 2218
Future aspirations and goals	0.11 (0.07, 0.14) 1080	0.15 (0.12, 0.17) 2218
Family support for learning	0.14 (0.11, 0.18) 1078	0.13 (0.10, 0.16) 2214

Total school engagement	0.21 (0.18, 0.25) 1082	0.23 (0.20, 0.25) 2221
(d) Strengths and difficulties		
Anxiety/ emotional problems	-0.51 (-0.53, -0.49) 3711	-0.23 (-0.26, -0.20) 1881
Peer relationship problems	-0.54 (-0.56, -0.53) 3710	-0.21 (-0.24, -0.18) 1880
Hyperactivity/ inattention	-0.36 (-0.38, -0.34) 3710	-0.33 (-0.35, -0.30) 1880
Conduct problems	-0.36 (-0.38, -0.33) 3711	-0.23 (-0.27, -0.20) 1880
Total behavioural difficulties	-0.64 (-0.65, -0.63) 3711	-0.38 (-0.41, -0.35) 1881
Prosocial behaviour	0.36 (0.34, 0.38) 3711	0.35 (0.32, 0.38) 1880

Note. Number of complete pairs of twins is given with each correlation. Colour of cell indicates strength of correlation, with blue indicating a correlation of -1, white no correlation and red a correlation of 1.

4.4.3 *Correlations with related measures: the 14 wellbeing indicators*

There is specificity in terms of magnitude of the correlations across the wellbeing indicators, as shown in Appendix 4.1, but often the confidence intervals overlap, especially within indicators that load onto the same component from the PCA. Life satisfaction demonstrated the strongest correlations with most life outcomes. Subjective happiness had lower correlations than life satisfaction for all measures except neuroticism and extraversion, indicating that measuring the components of subjective wellbeing separately can help us understand additional nuance. As would be expected, relatedness had stronger correlations with peer relationship problems than the subjective wellbeing indicators. Most of the basic psychological needs (autonomy, related and competence) showed similar correlations as subjective wellbeing across all life outcomes. Both our subjective wellbeing indicators and the basic psychological needs loaded strongly onto our *flourishing* component.

Curiosity and subjective health showed weaker associations with most of the life outcomes. It is possible that during adolescence, a generally curious disposition may lead to pleasant outcomes (Wootton, Davis, Mottershaw, Wang, & Haworth, 2017), but also to distress, resulting in a neutral impact on wellbeing. The exception to curiosity's weak correlations was the moderate association with openness, though curiosity has been defined as a subordinate factor of openness (Kashdan, Rose, & Fincham, 2004) which may explain this relationship. Subjective health was measured with a single item and responses were skewed with most individuals rating their health favourably, which may explain the weaker correlations observed. We would expect adolescents to rate health favourably as physical health is seldom an issue during adolescence. However, trust was also a single item measure that most participants endorsed and has associations comparable to the other wellbeing indicators. Furthermore, subjective health did not load onto either of our PCA components. As curiosity and subjective health did not show the same correlational patterns as the other positive traits, it is likely these traits are correlates of wellbeing rather than direct wellbeing indicators.

Across the life outcomes, interesting patterns emerged. First, peer relationships had higher correlations than parental measures, supporting the importance of peers over family relationships in adolescence (Park, 2004; Wang et al., 2017). Parental control was only weakly associated with autonomy (0.11), which we expected to be stronger given a lower score on parental control indicated that parents make most of their child's decisions. Furthermore, the lack of association with our two wellbeing components suggest that parental control is not an important factor in adolescent wellbeing. Second, agreeableness was weakly correlated with most wellbeing indicators, though had modest correlations with gratitude, life satisfaction, and subjective happiness. As agreeableness involves social interaction, we may expect stronger correlations with more social wellbeing indicators such as relatedness. Finally, the associations between our wellbeing components and our wellbeing indicators and school engagement are reasonably large considering some of the school measures assess environments rather than psychological states. It is surprising that 'future aspirations and goals' is not more highly associated with hopefulness as the scale contains items specifically relating to hopefulness. It is possible our hopefulness measure captures a global hopefulness rather than being specific to the school environment, though this requires further exploration.

4.4.4 *Limitations and Future Directions*

A major strength of our study was that we collected data on 14 diverse wellbeing indicators in the same, large sample. These were collected as part of a larger study of adolescent development. In two cases we had to shorten the published version of the scale to fit the space constraints of the overall study. However, the shortened measures showed good reliability in our sample (Cronbach's alphas = 0.86 for life satisfaction and 0.82 for meaning in life), and the correlations with other measures are in the expected direction, so we are confident that we assessed the same construct as the full scale. Data were collected using a mixture of online and booklet questionnaires, with an average six-month gap between the online study and the postal study. This gap in data collection may have reduced the inter-correlations between measures in the online study and the booklet, though the similarity in correlations across the data collection methods suggests this has not affected the correlations substantially. Of note, the same subjective happiness scale was used in both the online and postal studies, and the correlation between these measures was 0.67 (n= 1,884 pairs of twins), indicating good test-retest reliability.

Of course, there are also additional traits that could be considered eudaimonic wellbeing indicators that we were not able to include in the data collection. I identified 38 different components across the instruments from my critical review in Chapter 1 (see Appendix 1.3). The eudaimonic wellbeing indicators included in TEDS are not diverse enough to represent all of these measures. For example, previous positive traits included as eudaimonic wellbeing indicators are composure, calmness and wisdom, though it is not understood whether such traits are actually indicators of eudaimonic wellbeing. We do not intend for this analysis to be the definitive exploration of subjective and eudaimonic wellbeing in adolescence, but rather a first look at the diversity of adolescent wellbeing. We hope that this exploration will stimulate others to investigate more nuanced relationships concerning wellbeing, and that others may begin to collect data that incorporates diverse aspects of eudaimonic wellbeing.

A limitation of our study is that we have relied upon self-reports. Future work would benefit from using multiple informants where possible, and more objective measures of positive behaviour and experience. In addition, our related outcome measures were all contemporaneous, so future studies should consider longer-term relationships between wellbeing and other important life outcomes, especially as these young people leave the family home and enter the workplace in young adulthood.

Finally, it may be considered a limitation that we used a sample of twins, rather than singletons. However, there is no reason to expect twins to differ from singletons on measures of wellbeing, and we corrected for relatedness in all of our analyses.

4.5 Chapter Summary

In this chapter, we explored the relationship between subjective and eudaimonic wellbeing indicators in adolescence and how these relate to different life outcomes. The relationship between our wellbeing indicators was partly explained by two overarching components, which we have described as *flourishing* and *aspirational drive*. *Flourishing* included wellbeing indicators representing both subjective and eudaimonic wellbeing and *aspirational drive* included eudaimonic wellbeing indicators related to cognitive functioning.

We suggest that structuring wellbeing as an overarching construct is appropriate in adolescence, but it does not follow the theoretical distinction of subjective and eudaimonic wellbeing.

Together, our two wellbeing components explained just over half (54%) of the variance, indicating that wellbeing in adolescence is complex. This complexity was further highlighted when we explored how our wellbeing components and our diverse wellbeing indicators related to measures of relationships, personality, school engagement and behaviour. Wellbeing is multifaceted, and future studies should try to use a range of subjective and eudaimonic indicators to examine the depth and diversity of wellbeing in everyday lives. The next chapter builds on this analysis to explore the genetic and environmental influences that drive the observed phenotypic relationships between our wellbeing components. It is of interest to understand how genetically similar different aspects of subjective and eudaimonic wellbeing are, and whether the genetic and environmental similarities show the same pattern of relatedness observed phenotypically.

Chapter 5. Genetic and environmental correlations between diverse measures of wellbeing in adolescence

5.1. Chapter Overview

In Chapter 4, I applied principal components analysis (PCA) to explore the relatedness between subjective and eudaimonic wellbeing indicators in adolescence. I also assessed the similarities between the wellbeing indicators by examining the relationship between the indicators and important life outcomes. I concluded that the phenotypic relationship between the wellbeing indicators was complex, but 54% of the variance could be explained by two general PCA components, termed *flourishing* and *aspirational drive*. The first component captured both subjective and eudaimonic wellbeing, suggesting that wellbeing can be considered as an overarching construct for these theoretically distinct components. The second component captured cognitive eudaimonic traits, which represent a component of wellbeing associated with a fulfilling potential.

This chapter extends the phenotypic analysis to explore the genetic and environmental relatedness between our two wellbeing components. Previous research suggests that there is likely stronger genetic overlap than environmental overlap between wellbeing indicators (Caprara et al., 2009; Haworth, Carter, Eley, & Plomin, 2015), but no research to date has explored the aetiological relationship between subjective wellbeing and such a detailed range of eudaimonic wellbeing indicators. Consequently, I first modelled the aetiological relationship between our two wellbeing components, then estimated the genetic and environmental correlations between the two subjective wellbeing and 12 eudaimonic wellbeing indicators using data from the Twins Early Development Study (TEDS). Finally, I characterised the genetic and environmental relatedness between the wellbeing indicators using PCA.

In this chapter I aim to:

1. Estimate the variation in our two wellbeing components and in each wellbeing indicator explained by genetic and environmental influences.
2. Understand the genetic and environmental overlap between our two wellbeing components and between diverse wellbeing indicators during adolescence.
3. Characterise the genetic and environmental relationship between the subjective and eudaimonic wellbeing indicators using principle components analysis.

5.2.Introduction

As discussed in Chapter 2 (section 2.2), individual variation in wellbeing has been attributed to both genetic and environmental influences across a range of subjective and eudaimonic wellbeing indicators (Bartels, 2015; Bartels et al., 2010; Nes et al., 2013). However, few studies have explored the genetic and environmental overlap between subjective and eudaimonic wellbeing indicators with an adolescent sample, and so far studies have only used a few measures of eudaimonic traits. Here, we aim to understand the aetiological influences on wellbeing in more detail by exploring a diverse range of subjective and eudaimonic wellbeing indicators in a large twin cohort.

5.2.1. Multivariate genetic analysis

Multivariate genetic analysis allows us to estimate the relative contributions of genetic and environmental influences to the covariance between traits (Plomin, DeFries, Knopik, &

Neiderheiser, 2013). This is useful to determine the extent to which genetic or environmental influences drive the phenotypic correlations we observe. Across a variety of psychological traits, multivariate genetic analyses have shown that genetic influences substantially overlap, which suggests that the genetic influences associated with one trait are likely associated with another. This has been investigated for cognitive traits including intelligence (Trzaskowski, Shakeshaft, & Plomin, 2013), learning abilities and disabilities (Davis, Haworth, & Plomin, 2009; Haworth et al., 2009; Plomin & Kovas, 2005); negative mental health outcomes such as anxiety and depression (Kendler, Neale, Kessler, Heath, & Eaves, 1992) and internalising and externalising behaviour (Eley, 1997); and for wellbeing assessed as subjective, psychological and eudaimonic wellbeing (Bartels & Boomsma, 2009; Gatt, Burton, Schofield, Bryant, & Williams, 2014; Gigantesco et al., 2011; Haworth et al., 2015). In contrast, the environmental overlap between such traits is consistently much lower (Davis et al., 2009; Gatt et al., 2014; Haworth et al., 2009), which suggests environmental influences are largely trait specific.

The genetic and environmental overlap between traits can be assessed using two statistics: bivariate heritability and genetic (or nonshared environmental) correlations (see section 2.2). Bivariate heritability estimates the proportion of the phenotypic correlation between two traits that can be accounted for by shared genetic influences. The genetic correlation provides an estimate of the extent that the genetic influences that affect one trait correlate with the genetic influences that affect a second trait, independent of the heritability estimates of the traits (Plomin et al., 2013). Four studies have investigated the genetic and environmental overlap between subjective and eudaimonic wellbeing indicators in adolescence.

5.2.2. Genetic and environmental overlap in wellbeing

Across both subjective wellbeing and eudaimonic wellbeing indicators, the genetic overlap is usually high (genetic correlation, rG > 0.70), whereas estimates of the environmental overlap are much lower (environmental correlation, rE usually < 0.50). Subjective wellbeing has been explored using measures of happiness and life satisfaction in two studies (Bartels & Boomsma, 2009; Haworth et al., 2015). Both report estimates of bivariate heritability around 50%, suggesting genetic and environmental influences are equally important to the phenotypic relationship. The genetic overlap in subjective wellbeing indicators has been estimated at 0.77 (Haworth et al., 2015), which is similar to estimates of the genetic overlap in eudaimonic wellbeing indicators using measures of Ryff's (1989) six scales of psychological wellbeing, self-esteem and optimism (rG > 0.77; Gigantesco et al., 2011; Caprara et al., 2009).

The shared aetiology between subjective wellbeing and eudaimonic wellbeing has been explored in one twin study using measures of life satisfaction as a component of subjective wellbeing, and optimism and self-esteem as components of eudaimonic wellbeing (Caprara et al., 2009). They found genetic correlations of 0.80 between life satisfaction and self-esteem and 0.87 between life satisfaction and optimism, and much lower environmental correlations (0.18 and 0.32 respectively). Furthermore, a recent preprint of a molecular genetic study of subjective wellbeing (measured as happiness) and eudaimonic wellbeing (measured as meaning in life) reported a genetic correlation of 0.78 (Baselmans & Bartels, 2018), which indicates the common genetic variants on subjective and eudaimonic wellbeing largely overlap. However, studies of the genetic and environmental overlap between subjective wellbeing and diverse wellbeing indicators have so far been limited. I address this issue by providing both genetic correlations and bivariate heritability estimates for a range of subjective and eudaimonic wellbeing indicators.

5.2.3. Assessing the genetic and environmental similarities across our wellbeing indicators

In addition to estimating the genetic and environmental correlations and shared heritability estimates across two traits, multivariate genetic analysis can be used to model the genetic and environmental aetiology across multiple traits. This is useful to determine the extent to which genetic influences are shared across traits, and determine whether genetic (and environmental) influences are better modelled by independent pathways or by one common underlying factor (Plomin et al., 2013). For example, a Cholesky decomposition has been used to demonstrate the extent that genetic and environmental influences on subjective wellbeing go beyond the genetic and environmental influences on negative mental health outcomes (Haworth et al., 2015), suggesting that subjective wellbeing is more than the absence of mental illness. Correlated factors models have previously been applied to subjective wellbeing indicators (Bartels & Boomsma, 2009) and subjective and eudaimonic wellbeing indicators (Caprara et al., 2009; Keyes, Myers, & Kendler, 2010). In two studies, it appeared that an independent pathways model fit better than a common pathways model, suggesting that the genetic influences on each of the traits operated through distinct systems (Bartels & Boomsma, 2009; Caprara et al., 2009). However, one study found the best fitting model for emotional wellbeing, social wellbeing and psychological wellbeing was a common pathways model (Keyes et al., 2010), suggesting there is a higher-order factor of wellbeing that encompasses multiple wellbeing components.

Here, I assessed the aetiological relationship between the two components that emerged from the PCA analysis in Chapter 4. This allowed me to assess the relationship between our diverse representation of wellbeing without the need for multivariate twin analyses. I also explored the relationship between the individual wellbeing indicators. It would be useful to apply multivariate genetic analyses to our diverse wellbeing indicators to determine whether there is one underlying construct. However, a model with 14 traits would be difficult to optimise and impossible to interpret. Instead, I used principle components analysis to characterise the genetic and environmental overlap across the wellbeing indicators and compared this to our wellbeing components derived phenotypically in Chapter 4. This is the first study to focus on understanding the common genetic and environmental aetiologies in such a wide range of wellbeing indicators. It is also the first study to explore these aetiological relationships during adolescence.

5.3.Method

5.3.1. Measures

Data was collected as part of the Twins Early Development Study, as described in Chapter 3, section 3.1. Here, we used wellbeing data from 10,915 individuals including 5,302 complete twin pairs (1,931 monozygotic and 3,371 dizygotic pairs). We used nine measures (life satisfaction, subjective happiness, optimism, gratitude, hopefulness, grit, ambition, curiosity, and subjective health) from the web study and seven measures (life satisfaction, subjective happiness, autonomy, competence, relatedness, meaning in life, and trust) from the booklet study. Life satisfaction and subjective happiness were considered as indicators of subjective wellbeing, and the other 12 traits were considered as indicators of eudaimonic wellbeing. Life satisfaction and subjective happiness measures were included in both data collection methods; when participants had responses for both, the mean score was taken. As described in Chapter 4, composites for the two wellbeing components were derived by creating a mean score of the traits that loaded onto each component. All measures were scaled before creating a mean to ensure they were given equal weighting. A participant needed to have data for at least 50% of the measures to be included the in composite. The *flourishing* component of wellbeing included life satisfaction, subjective happiness, relatedness, autonomy, competence, gratitude, optimism, meaning in life and trust. Trust was treated as a numeric variable for inclusion. *Aspirational drive* included hopefulness, ambition, grit, curiosity and gratitude.

5.3.2. Data Analyses

Data analyses consisted of two steps: first using structural equation modelling of twin data to generate correlation matrices for the genetic and environmental components of the wellbeing components and the individual wellbeing indicators; and second performing principal components analyses (PCA) on each matrix for the individual wellbeing indicators. Rather than running a single model with 14 different outcomes, which would be difficult to optimise and challenging to interpret, we ran a series of bivariate models and extracted the genetic and environmental correlations from these models. We also extracted the proportion of the phenotypic correlations explained by the genetic and environmental influences to provide context to our interpretations. The PCA on the genetic and environmental correlation matrices allowed us to visualise the results to highlight clusters of measures that are more strongly related for genetic or environmental reasons (Davis &

Plomin, 2010). We were then able to compare the components that emerged with our wellbeing components from the phenotypic PCA in Chapter 4.

5.3.2.1. Twin analyses

Standard twin model-fitting analyses were conducted using the OpenMx package (Neale et al., 2015) in R. We used full-information maximum likelihood estimation to incorporate all data, including data from incomplete twin pairs. Our analyses were adjusted for the effects of age and sex. First, I ran univariate analyses for the two wellbeing components and the 14 wellbeing indicators. The univariate analyses for the 14 wellbeing was conducted in collaboration with Robyn Wootton, as a member of our lab group. I then ran bivariate Cholesky decompositions for the two wellbeing components (*flourishing and aspirational drive*) and each combination of the wellbeing indicators, which allowed us to decompose the covariance between each of the indicators into genetic and environmental influences. The Cholesky decomposition provides complete estimates of genetic (A), shared environmental (C) and nonshared environmental (E) influences for the first measure added to the model, then decomposes how much variance of the first trait accounts for variance of A, C and E in the second trait, then estimates the remaining variance in the second trait. As the Cholesky decomposition depends on the order that the measures are added to the model, we converted the Cholesky model to the mathematically equivalent correlated factors solution to calculate the correlations between the genetic and environmental influences. Bivariate models provide estimates for the A, C and E components of variance for each trait as well as the covariance between two traits. I used the bivariate models to estimate the univariate A, C and E estimates for each of the wellbeing measures. This provides more power than running univariate twin models.

The estimates for trust were computed using a liability threshold model. A liability threshold model allows analysis of measures with a dichotomous response by estimating the underlying distribution of the trait liability within the population. The bivariate liability threshold model allows analysis of a dichotomous measure and a continuous measure by combining a means model and a liability threshold model. A more detailed description of twin modelling is provided in Chapter 3, section 3.2.1.

5.3.2.2. Principal components analysis

After we had estimated genetic and environmental correlations for each pair of our wellbeing indicators, we used principal components analysis with Varimax rotation to produce graphical representations of the underlying genetic and environmental structure between the measures. This reduced the high-dimensional relationships among the measures to a small number of spatial components. We decided on the number of components to extract by the number of eigenvalues less than one, the elbow on the scree plot, and by parallel analysis (Horn, 1965). The measures were considered to load onto a component if the loading was greater than 0.45 (explaining 20% of the variance). Reasoning behind these methodological decisions is provided in Chapter 3, section 3.2.2.1.

5.4.Results

Here, I first present the results for the wellbeing components, *flourishing* and *aspirational drive*. Then I discuss the results for the 14 individual wellbeing indicators.

5.4.1 The aetiological relationship between the two wellbeing components

First, I assessed whether there were differences in sex or zygosity for *flourishing* and *aspirational drive*. As shown in Table 5.1, there were no mean differences across sex or zygosity for our wellbeing components. As discussed in Chapter 3 (Section 3.2.1 and Appendix 3.3), the ACE model is compared to a saturated model to check that the ACE model does not fit significantly worse than the saturated model. For both components, the ACE model did not fit significantly worse that the saturated Gaussian model (Table 5.2). Therefore, we modelled ACE models for both wellbeing components. This allowed us to estimate the genetic, shared environmental and nonshared environmental influences whilst controlling for age and sex, and assuming equal means and variances across twin order and zygosity.

The univariate estimates of the genetic (A), shared environmental (C) and nonshared environmental (E) influences for the two wellbeing components are reported in Table 5.3. For both components, shared environmental influences did not explain any variance. Additive genetic influences explained more variance in *flourishing* than nonshared environmental influences, where genetic influences explained 58% of the variance. In contrast, 52% of the variance in *aspirational drive* was explained by nonshared environmental influences, whereas only 48% was explained by genetic influences. These results suggest that genetic and nonshared environmental influences are both substantially important to the variation in wellbeing across adolescence.

Table 5.1 Means (SD), N and ANOVA results for effect of sex and zygosity on the wellbeing components.

	All	MZ	DZ	Male	Female	Sex p-value	Sex effect size	Zygosity p-value	Zygosity effect size
Flourishing	0.00 (1.00) 3743	0.02 (1.02) 1335	-0.01 (0.99) 2408	0.00 (0.94) 1734	0.00 (1.05) 2009	0.97	3.9×10^{-7}	0.27	0.0003
Aspirational drive	0.00 (1.00) 2662	0.01 (1.02) 1007	-0.01 (0.99) 1655	0.04 (0.98) 1115	-0.03 (1.02) 1547	0.08	0.001	0.69	5.81×10^{-5}

Note: N refers to one randomly selected member of each twin pair to avoid non-independent observations; effect size=eta squared.

Table 5.2 Model comparisons for the saturated model and the ACE model, for the two wellbeing components.

	Base model	Comparison	EP	-2 Log likelihood	Degrees of freedom	Δ-2LL	Δdf	*p*
Wellbeing components								
Flourishing	Saturated		9	46140.58	7456			
	Saturated	ACE	6	46145.76	7459	5.18	3	0.16
Aspirational drive	Saturated		9	26634.54	5081			
	Saturated	ACE	6	26637.25	5084	2.71	3	0.44

Note. EP refers to number of estimated parameters in model, Δ-2LL refers to difference in Log likelihood, Δdf refers to difference in degrees of freedom.

Next, I ran a bivariate ACE model to assess the aetiological relationship between our two wellbeing components. It may seem more parsimonious to run bivariate AE models (which constrain C to zero). However, this would inflate genetic estimates if any shared environment is present. As the confidence intervals for C are greater than zero, we cannot rule out the presence of shared environmental influences.

The phenotypic correlation between the two wellbeing components was moderate (0.60; 95% confidence intervals = 0.58 to 0.62). The genetic correlation was higher (0.72; 0.65 to 0.84) and the nonshared environmental correlation was lower (0.49; 0.43 to 0.54). This suggests substantial genetic overlap between *flourishing* and *aspirational drive*. Furthermore, shared genetic influences explained more of the phenotypic correlation than nonshared environmental influences (bivariate heritability = 0.62; 95% Cis = 0.61 to 0.69; nonshared environmental influences = 0.39; 0.36 to 0.40). This suggests that genetic influences play a greater role than nonshared environmental influences in the observed similarity in the wellbeing components.

Table 5.3 The genetic (A), shared environment (C) and nonshared environment (E) univariate parameter estimates with 95% confidence intervals for the two wellbeing components.

	Twin model estimates		
	A	**C**	**E**
Wellbeing components			
Flourishing	0.58 (0.52; 0.61)	0.00 (0.00; 0.05)	0.42 (0.39; 0.45)
Aspirational drive	0.48 (0.35; 0.53)	0.01 (0.00; 0.11)	0.52 (0.47; 0.56)

5.4.2 The aetiological relationship between the 14 wellbeing indicators

There were mean sex differences for all of the wellbeing indicators except competence, subjective happiness, and meaning in life and mean differences between monozygotic and dizygotic twins for curiosity and grit (see Table 3.3). The effect of all these differences were small, and I chose to run a single model across sex. For the 14 wellbeing indicators, the ACE model did not fit significantly worse than a saturated Gaussian model (Appendix 5.1). Consequently, for all the wellbeing indicators, we again used ACE models to estimate the genetic, shared environmental and nonshared environmental influences whilst controlling for age and sex, and assuming equal means and variances across twin order and zygosity.

The univariate estimates of the genetic (A), shared environmental (C) and nonshared environmental (E) influences for each measure are reported in Appendix 5.2. The nonshared environmental influences explain more of the variation in most of the wellbeing indicators (mean = 0.57) than genetic influences (mean = 0.42), with no observable differences across the subjective and eudaimonic wellbeing indicators. Only a small influence of C was found for life satisfaction (0.10) and gratitude (0.04). Consequently, although we ran bivariate ACE models, only the genetic and nonshared environmental correlation matrices were explored using PCA.

5.4.2.1 Genetic and environmental overlap between the wellbeing indicators

The genetic correlations (Upper triangle of Appendix 5.3) are moderate (mean = 0.56), indicating shared genetic influences may be driving the phenotypic relatedness of the measures. This is emphasised in the high bivariate heritabilities (>0.50), displayed in the lower triangle of Table 5.3 (see Table 4.1 for phenotypic correlations). The strongest genetic correlation is between hopefulness and meaning in life (0.91) suggesting that these indicators have similar genetic aetiologies. Similarly, life satisfaction, relatedness, autonomy, competence and subjective happiness show high genetic correlations with each other. In contrast, the lowest genetic correlation of 0.16 suggests curiosity and subjective health share little genetic influence. Generally, curiosity has the weakest genetic correlations with the other wellbeing indicators. These genetic correlations seem to mirror the patterns observed in the phenotypic correlations in Chapter 4, though the genetic correlations are generally greater in magnitude.

The average genetic correlation between the booklet measures (relatedness, autonomy, competence, meaning and trust) was moderate (0.65), though the average genetic correlation between the web measures (optimism, gratitude, hopefulness, grit, ambition, curiosity and subjective health) was lower (0.51). This reflects the pattern observed phenotypically and we expected higher average correlations on the booklet because three measures were subscales of the basic psychological needs satisfaction scale. The average genetic correlation across the web and the booklet measures was 0.51, which is equal to the genetic correlation between the web measures. This suggests that the correlations are similar within and across data collection methods. However, it is difficult to draw strong conclusions because the specific wellbeing indicators differ across data collection.

In comparison to the genetic correlations, the correlations between the nonshared environmental influences on the wellbeing indicators are weaker and ranged from -0.07 to 0.51 (mean = 0.25) (Upper triangle of Appendix 5.4). Some nonshared environmental correlations are notably low (< 0.10), including between trust and the measures of hopefulness, ambition, curiosity, and subjective health; curiosity and relatedness, autonomy, meaning in life; and grit and health. The strongest nonshared environmental correlation is between autonomy and relatedness (0.51). Life satisfaction, relatedness, autonomy, competence, subjective happiness and meaning in life show moderate correlations (0.34 to 0.51) with each other. The proportion of the phenotypic correlation explained by the overlap of nonshared environmental influences (lower triangle of Table 5.4) are all under 0.52, with most making only modest contributions to explaining the phenotypic correlation (mean = 0.34).

The average nonshared environmental correlation between the booklet measures (relatedness, autonomy, competence, meaning and trust) was modest (0.37) and the average nonshared environmental correlation between the web measures (optimism, gratitude, hopefulness, grit, ambition, curiosity and subjective health) was lower (0.23). Furthermore, the average nonshared environmental correlation across the web and the booklet measures was even lower (0.17), suggesting that the data collection method may have confounded the associations we observe.

5.4.2.2 Principal components analysis

We used principal components analysis to reduce the high-dimensional relationships among the indicators to a small number of spatial components. Considering the eigenvalues, scree plot and parallel analysis, we extracted two components for the genetic correlation matrix and three principal components for the nonshared environmental correlation matrix. The loadings onto the components are displayed in Table 5.4.

Table 5.4 The genetic and nonshared environmental component loadings and proportion of variance explained by each component for the 14 positive psychological measures.

	Genetic loadings		**Nonshared environmental loadings**		
	Component One	Component Two	Component One	Component Two	Component Three
Life Satisfaction	**0.91**	0.26	**0.57**	**0.51**	0.21
Subjective Happiness	**0.85**	0.23	**0.50**	**0.54**	0.07
Relatedness (b)	**0.86**	0.19	**0.73**	0.21	-0.03
Autonomy (b)	**0.83**	0.14	**0.72**	0.14	0.04
Competence (b)	**0.75**	**0.53**	**0.67**	0.16	0.11
Gratitude (w)	**0.72**	0.35	0.17	**0.56**	0.29
Optimism (w)	**0.71**	0.40	0.42	0.10	0.38
Meaning in life (b)	**0.64**	**0.59**	**0.57**	0.30	0.21
Trust (b)	**0.68**	0.14	**0.61**	-0.12	0.07
Hopefulness (w)	**0.61**	**0.73**	0.13	**0.57**	**0.52**
Ambition (w)	0.24	**0.87**	0.05	0.14	**0.76**
Grit (w)	0.34	**0.70**	0.35	-0.24	**0.65**
Curiosity (w)	0.05	**0.79**	-0.07	0.34	**0.59**
Subjective Health (w)	**0.56**	0.29	0.07	**0.60**	-0.03
Proportion of variance explained	0.45	0.26	0.22	0.14	0.14

Note: The number of components to extract was decided by the number of eigenvalues less than one, the elbow on the scree plot, and parallel analysis. (b) indicates measures collected on the booklet, (w) indicates measures collected on the web.

The genetic loadings are strong (>0.55) onto component 1 for all indicators except ambition, grit and curiosity. Component 2 has strong loadings from six measures: competence (0.53), meaning in life (0.59), hopefulness (0.73), ambition (0.87), curiosity (0.79) and grit (0.70). The measures of competence, meaning in life and hopefulness are complex, loading above 0.50 on both components. These results are represented in Figure 5.1, where the axes are the components from the PCA that was performed using the genetic correlation matrix. In Figure 5.1, genetically similar wellbeing indicators are in closer proximity and genetically dissimilar indicators are further away. For example, the closest positioning between subjective happiness and life satisfaction represents a genetic correlation of 0.85, whereas the distance between autonomy and curiosity represents a genetic correlation of 0.21. Taken together, the two components explain 71% of the variance in the genetic correlations.

In the nonshared environmental PCA, seven wellbeing indicators loaded onto component 1: life satisfaction (0.57), relatedness (0.73), autonomy (0.72), competence (0.67), subjective happiness (0.50), trust (0.61) and meaning in life (0.57). Component 2 is defined by life satisfaction (0.51), subjective happiness (0.54), gratitude (0.56), hopefulness (0.57) and subjective health (0.60). The third component has loadings from hopefulness (0.52), ambition (0.76), curiosity (0.59) and grit (0.65). Life satisfaction, subjective happiness and hopefulness are complex, with high loadings on two components. Optimism failed to load onto any component. The PCA for the nonshared environmental correlations for the wellbeing indicators is visualised in Figure 5.2. Competence, autonomy and relatedness (the three basic psychological needs) are positioned closely across all of the components, suggesting these measures overlap in the nonshared environmental influences more so than with other wellbeing indicators, such as ambition, which is positioned further away across each panel in Figure 5.2. Together, the three components explained 50% of the variance in the nonshared environmental correlations.

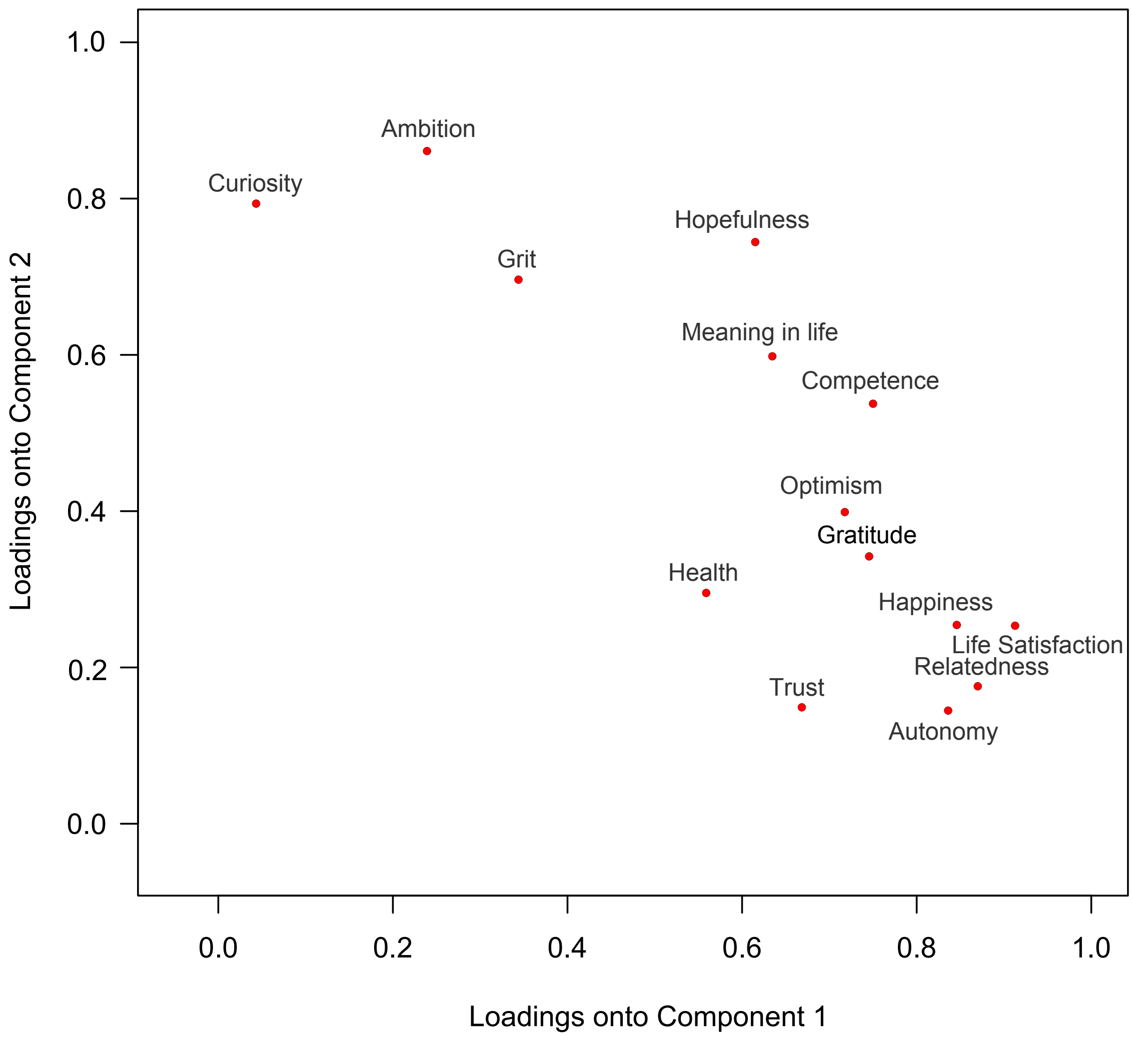


Figure 5.1 Plot of the genetic relationship between the 14 wellbeing indicators, with the principal components as axes. The scale represents the loadings onto each component, which can range between -1 and 1, where a positive loading indicates that measures are positively represented by the principal component. The relative positioning of the measures represents their genetic similarity. Similar measures are positioned closer together, and dissimilar measures are further apart.

Note: Life S. = Life Satisfaction; Happ. = Subjective Happiness; Rel. = Relatedness; Aut. = Autonomy; Comp. = Competence; Grat. = Gratitude; Opt. = Optimism; Mean. = Meaning in Life; Hope. = Hopefulness; Amb. = Ambition; Cur. = Curiosity, Health = Subjective Health. Number of complete pairs of twins ranged from 1010 to 5269. The proportions for curiosity and trust were calculated using absolute values, as the nonshared environmental correlation was negative.

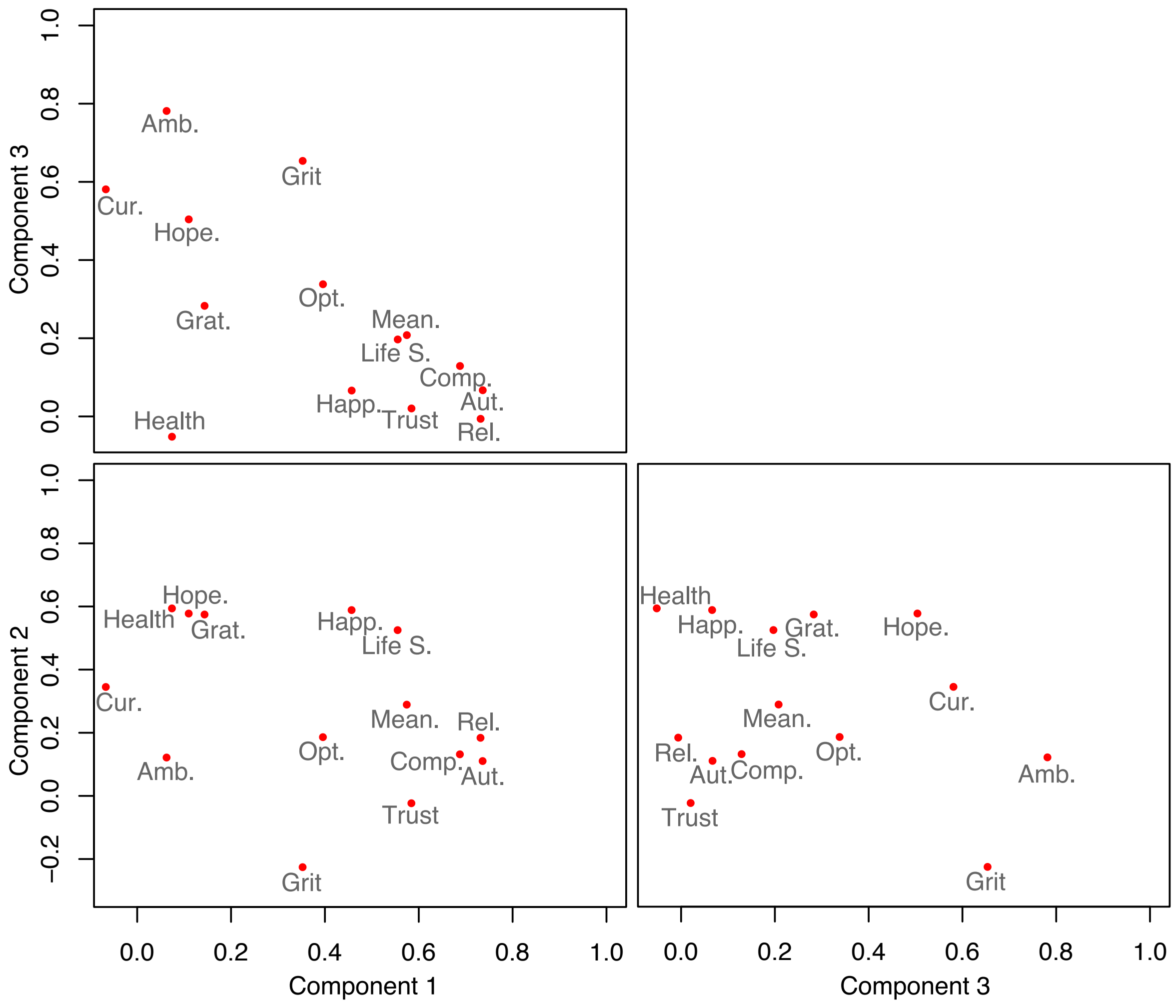


Figure 5.2 Plot of the nonshared environmental relationship between the 14 wellbeing indicators with the principal components as axes. The scale represents the loadings onto each component, which can range between -1 and 1, where a positive loading indicates that measures are positively represented by the principal component. The three panels show the relationship between the different components. The relative positioning of the measures represents their nonshared environmental similarity. Similar measures are positioned closer together, and dissimilar measures are further apart. For example, hopefulness and subjective health are positioned closely in the panel of components 1 and 2, and further apart in the other panels, suggesting that these measures are more similar in their loadings onto components 1 and 2, but are dissimilar in relation to component 3.

Note: Life S. = Life Satisfaction; Rel. = Relatedness; Aut. = Autonomy; Comp. = Competence; Happ. = Subjective Happiness; Mean. = Meaning in Life; Grat. = Gratitude; Opt. = Optimism; Hope. = Hopefulness; Amb. = Ambition; Cur. = Curiosity, Health = Subjective Health. Number of complete pairs of twins ranged from 1010 to 5269. The proportions for curiosity and trust were calculated using absolute values, as the nonshared environmental correlation was negative.

5.5. Discussion

Our results show substantial overlap between our wellbeing components and also emphasise the subtle patterns in the overlap between genetic and nonshared environmental influences among a wide range of subjective and eudaimonic wellbeing indicators in adolescence. Genetic influences on the wellbeing indicators are largely shared and explain more of the phenotypic correlation than nonshared environmental influences. Nonshared environmental influences explain more of the variation in each wellbeing indicator than genetic influences but are shared to a lesser extent between the wellbeing indicators. Our findings support previous research, which consistently finds more genetic overlap than environmental overlap between indicators of wellbeing (Archontaki, Lewis, & Bates, 2013; Caprara et al., 2009; Franz et al., 2012; Gigantesco et al., 2011; Haworth et al., 2015). Our research also supports a representation of wellbeing as an overarching construct (Disbato et al., 2016; Su et al., 2014), but suggests that the distinction between subjective and eudaimonic wellbeing is largely theoretical.

5.5.1. Shared genetic influences and specific nonshared environmental influences

Our *flourishing* and *aspirational drive* components had a high genetic correlation (0.72) whereas the nonshared environmental correlation was only moderate (0.49). Similarly, the average genetic correlation between the all of the wellbeing indicators was moderate (0.56) and the average nonshared environmental correlation was modest (0.25), suggesting genetic influences are largely shared and environmental influences are more trait-specific. This mirrors patterns from previous research using adolescent and adult samples (Archontaki et al., 2013; Franz et al., 2012; Gigantesco et al., 2011). However, the range of the genetic and nonshared environmental correlations in our study was large and our average genetic correlation was lower than previous research using eudaimonic indicators (Gigantesco et al., 2011; Caprara et al., 2009), which may reflect the diversity in the traits considered to represent eudaimonic wellbeing. Including only wellbeing indicators that loaded onto the *flourishing* component in Chapter 4, the average genetic correlation was 0.67 and the average nonshared environmental correlation was 0.33, which is comparable with previous research. This is higher than the correlations between the indicators that loaded onto aspirational drive (rA = 0.48; rE = 0.21).

We also found moderate genetic and environmental overlap between subjective wellbeing indicators and eudaimonic wellbeing indicators, suggesting that the distinction between subjective and eudaimonic wellbeing may be largely theoretical than empirical. The aetiological relationship between our subjective wellbeing indicators and our seven eudaimonic wellbeing indicators that loaded onto the *flourishing* component was strong (average rA = 0.71; average rE = 0.38). These estimates are comparable with previous studies (Baselmans & Bartels, 2018; Caprara et al., 2009) and have implications for molecular genetics. The use of multi-trait analysis of GWAS (MTAG; Turley et al., 2017), which uncovers specific genetic variants associated with different related traits, can be applied to wellbeing by combining more diverse eudaimonic wellbeing indicators. This will increase statistical power to detect genetic effects on each wellbeing indicator (Turley et al., 2017), as well as on wellbeing as an overarching construct. However, we need to ensure we are using diverse traits that are in fact wellbeing indicators because using traits that are correlates rather than composites of wellbeing could misidentify specific genetic variants associated with wellbeing.

5.5.2. The aetiological relationship between subjective wellbeing indicators

Our subjective wellbeing indicators (subjective happiness and life satisfaction) were strongly genetically correlated (0.85) and moderately correlated for nonshared environmental influences (0.47), which is in line with previous research using the same sample (Haworth et al., 2015). Subjective happiness and life satisfaction also have similar patterns of relationships with the other eudaimonic wellbeing indicators. The correlations between life satisfaction and the eudaimonic indicators are generally within 0.10 of the equivalent correlation between subjective happiness and the eudaimonic indicators. Their similarity is reflected in their comparable loadings onto the PCA components, and their close proximity in Figures 5.2 and 5.4. This suggests that as well as happiness and life satisfaction having similar genetic and environmental aetiologies, they also generally share the same degree of communality with the eudaimonic wellbeing indicators.

The apparent homogeneity between happiness and life satisfaction does not mean that there is no value in using two subjective wellbeing indicators instead of one. This is reflected in the genetic and environmental correlations, which are less than one, and in the univariate estimates where shared environmental influences (C) explained a proportion of the variation in life satisfaction but not in subjective happiness. Instead, it implies that factors driving the genetic and nonshared environmental overlap between these indicators also drive the observed relationship seen with the other wellbeing indicators. These findings are unlike the relationship between subjective wellbeing and mental illness, where there are different patterns of genetic overlap between life satisfaction and depression compared to happiness and depression using the same sample as this thesis (Haworth et al., 2015). This suggests the types of psychological traits being explored are important. Exploration of the types of psychological traits that show specificity in the genetic and nonshared environmental links with happiness and life satisfaction is required to truly understand the relationship between these subjective wellbeing indicators.

5.5.3. Characterising the relationship between subjective and eudaimonic wellbeing indicators

Using principal components analysis, we found that the genetic correlations between the wellbeing indicators were best explained by two components and the nonshared environmental correlations by three components. The PCA components also explained more variance in the genetic correlations (71% in total) than the nonshared environmental correlations (50% in total). These results suggest that the wellbeing indicators have additional environmental complexities that are not seen genetically. Our results are consistent with findings of a general factor for genetic influences and trait-specific nonshared environmental influences across wellbeing indicators (Archontaki et al., 2013; Keyes et al., 2010). Our results also support the generalist genes and specific environments hypothesis seen across a range of behavioural traits including learning disabilities and psychopathologies (Eley, 1997; Haworth et al., 2009; Trzaskowski et al., 2013).

The genetic relationship almost exactly mirrors the phenotypic relationship in Chapter 4. The first component in the genetic PCA additionally included hopefulness and subjective health along with the *flourishing* wellbeing indicators, but largely matched the phenotypic structure. However, two nonshared environmental components appeared to represent the phenotypic *flourishing* component. This additional environmental complexity could be due to measurement error, which is captured in the nonshared environmental influences in twin models (Plomin et al., 2013). It appears that these two environmental components for *flourishing* could represent the two forms of data collection. Life satisfaction, subjective happiness, relatedness, autonomy, competence, meaning in life and trust (component 1) were collected on the booklet, and life satisfaction, subjective happiness, gratitude, hopefulness and subjective health (component 2) were collected on the web. However, optimism, collected on the web, loads most strongly onto the environmental component 1 with the booklet measures which could suggest not all the environmental complexity is due to data collection.

The second genetic component and third nonshared environmental components were both similar to *aspirational drive*, though genetically competence and meaning in life also loaded onto this component as gratitude did not. This consistent grouping of the indicators across the phenotypic, genetic and environmental analyses suggests strong empirical evidence for a conceptualisation of wellbeing with multiple components that do not follow the theoretical distinction between subjective and eudaimonic wellbeing. Future research should explore the specific genetic and environmental influences that may be driving this pattern.

5.5.4. Limitations

First, a strength of our study is that we assessed diverse eudaimonic wellbeing traits captured using validated scales. It is difficult to compare estimates across different studies that use different types of wellbeing indicators. Consequently, we have discussed our subjective wellbeing indicators in more detail as these are likely of most value to other researchers, though there are nuances in the aetiological relationship across all our wellbeing indicators. Second, large multivariate models that included all our measures would enable us to interrogate the entire picture of the shared genetic influences and give a deeper understanding of how the measures are related. However, it would be difficult to order the measures in a meaningful way, and impossible to optimise. We instead used the graphical representation of the principal components analysis to reduce the high-dimensional relationships among the indicators to a small number of spatial components to outline potential similarities. We also used our wellbeing components from Chapter 4 to increase our understanding of the aetiological relationship between diverse components of wellbeing. Nevertheless, it could be useful to identify whether the wellbeing indicators from our *flourishing* component in Chapter 4 are best represented by correlated factors or an independent pathways model.

Third, the weaker nonshared environmental correlations in comparison to the genetic correlations may be explained by measurement error. Measurement error is reflected in the nonshared environmental component of each trait. This trait-specific measurement error could partly explain the weaker nonshared environmental correlations though would not explain the range of genetic correlations we observed. Some methods attempt to account for measurement error using reliability estimates such as test-retest reliability (Jang, McCrae, Angleitner, Riemann, & Livesley, 1998; McCrae, Kurtz, Yamagata, & Terracciano, 2011), but this approach assumes that any differences in measurement across time reflect measurement error instead of genuine changes in trait scores, which is not realistic. Future research would benefit from using other methods than self-reports to overcome the issue of measurement error, including multiple informants and objective measures of wellbeing.

5.6 Chapter summary

This chapter had three aims: first, to estimate the genetic and environmental influences on our two wellbeing components and on diverse wellbeing indicators in adolescence; second to understand the genetic and environmental overlap between our two wellbeing components and our diverse wellbeing indicators; and third to characterise the genetic and environmental relationship across the indicators. Our results show that genetic and nonshared environmental influences are equally important to *flourishing* and *aspirational drive* in adolescence. Our results also show that on average, nonshared environmental influences explain the most variance in each wellbeing indicator. It is therefore useful to explore the factors and life outcomes that may be specific nonshared environmental influences on wellbeing in adolescence. This will be addressed in the next chapter.

Our results also show substantial genetic overlap between our two wellbeing components and between the wellbeing indicators, which suggests research investigating specific genetic variants on wellbeing could combine diverse wellbeing indicators into a single wellbeing phenotype to improve power through increased sample size. We explained 71% of the variance in the genetic correlations and 50% of the variance in the nonshared environmental correlations with PCA analysis. The components that emerged for both the genetic and nonshared environmental influences were similar to our *flourishing* and *aspirational drive* components from the phenotypic analysis, showing strong evidence that these components are a good representation of wellbeing as an overarching construct. In comparison to the phenotypic PCA analysis in Chapter 4, we explained much more of the genetic variance and a similar proportion of the environmental variance between the wellbeing indicators. This suggests that there is less complexity in the way that the wellbeing indicators are related genetically compared to phenotypically and environmentally, and that environmental influences have more unique than general effects on wellbeing. It would therefore be useful to explore similarities and differences in the specific nonshared environmental influences across our wellbeing components and across diverse wellbeing indicators. The next chapter addresses the implications of these findings by exploring specific nonshared environmental influences on wellbeing using *flourishing*, *aspirational drive*, and the individual subjective and eudaimonic wellbeing indicators associated with our *flourishing* component.

Chapter 6. What matters most for adolescent wellbeing? An MZ twin differences study

6.1 Chapter Overview

The previous two chapters have explored the relationship between a range of subjective and eudaimonic wellbeing indicators in adolescence. Phenotypically, we found that our wellbeing indicators could be explained by two components: *flourishing* and *aspirational drive*. Chapter 5 explored the genetic and environmental aetiologies of *flourishing* and *aspirational drive* and of the 14 wellbeing indicators. I found that genetic and nonshared environmental influences are equally important to *flourishing* and *aspirational drive* and that nonshared environmental influences were responsible for most of the variation in each of the indicators. Using bivariate analyses, I showed that there was strong genetic overall between *flourishing* and *aspirational drive* as well as lower, but still moderate overall between the nonshared environmental influences. I also found moderate to strong genetic overlap between the wellbeing indicators, whereas the nonshared environmental influences were more trait-specific. This indicated that we should explore the specific environmental influences on the wellbeing indicators. Here, I use an MZ twin differences design to assess four environmental domains as specific environmental influences on wellbeing in adolescence. I characterise wellbeing as *flourishing* and *aspirational drive* from Chapter 4, and additionally used eight wellbeing indicators from the *flourishing* component to explore differences in the theoretically distinct concepts of subjective and eudaimonic wellbeing. This is the first study to use an MZ differences design to explore wellbeing in adolescence using such a diverse range of measures.

In this chapter I aim to:

1. Identify specific environmental influences associated with our *flourishing* and *aspirational drive* wellbeing components and with subjective and eudaimonic wellbeing in adolescence.
2. Explore any specificity in the nonshared environmental influences across the eight wellbeing indicators.

6.2 Introduction

Nonshared environmental influences are responsible for more of the variation in wellbeing than genetic influences. Across 70 genetically informative studies, 58% of the variation in wellbeing was due to nonshared environmental influences (Bartels, 2015) and estimates are similar for adolescent wellbeing (Bartels, Cacioppo, van Beijsterveldt, & Boomsma, 2013; De Neve, Christakis, Fowler, & Frey, 2012; Haworth, Carter, Eley, & Plomin, 2015; Nes et al., 2013; Røysamb, Harris, Magnus, Vittersø, & Tambs, 2002). Results for wellbeing are representative of nonshared environmental influences on diverse behavioural traits, with a meta-analysis of twin research indicating around 34% of the variance in behavioural traits can be attributed to the nonshared environment (Polderman et al., 2015). This suggests that significant research effort should be invested into identifying the specific environmental experiences and exposures that drive this effect, while controlling for any genetic confounding.

Recent and considerable effort from large consortia has begun to identify specific genetic variants that influence wellbeing. The Social Science Genetics Association Consortium (SSGAC) pooled data from 59 cohorts (almost 300,000 individuals) and identified three genetic variants that each explain less than 0.01% of the variance in subjective wellbeing (Okbay et al., 2016). Further investigation using genome-wide association analyses has explained approximately 6% of the variance in both subjective wellbeing (measured as happiness) and eudaimonic wellbeing (measured as meaning in life) (Baselmans & Bartels, 2018). In contrast, research focused on investigating the specific environmental factors that affect wellbeing (beyond the effect of genetic factors) has received less attention, despite nonshared environmental influences having the potential to explain more variance.

6.2.1 Identifying specific nonshared environmental influences

Specific nonshared environmental influences on wellbeing can be established using monozygotic (MZ) twins. As MZ twins share all of their genes and all of their shared environment (such as the shared effects of the family environment), any within-pair discordance must be due to nonshared environmental influences. The MZ differences design is a powerful tool for identifying specific aspects of the nonshared environment that can account for differences within MZ pairs while controlling for any genetic confounding, including gene-environment interplay (Viding, Fontaine, Oliver, & Plomin, 2009). This allows us to test the correlation between within-pair differences in environmental exposures and experiences and within-pair differences in outcomes, known as an MZ differences correlation.

Previous MZ differences studies have successfully identified specific nonshared environmental factors for a range of behavioural traits (Asbury, Almeida, Hibel, Harlaar, & Plomin, 2008; Oliver, Pike, & Plomin, 2008; Turkheimer & Waldron, 2000). These specific nonshared environmental effects typically explain 1 to 5% of the total variance in these behavioural outcomes (Turkheimer & Waldron, 2000), which is already comparable with the variance in wellbeing explained so far by specific genetic variants. Only one study has used an MZ differences design with implications for wellbeing during adolescence (Asbury, Moran, & Plomin, 2017). This qualitative MZ differences study, which used open-ended questions to explore within-pair discordance in peer relationships, identified peer victimisation as a potential nonshared environmental influence on mental health and wellbeing and advocated the need for further investigation (Asbury et al., 2017).

More studies have used the MZ twin differences design to explore specific nonshared environmental influences on negative mental health outcomes. Although negative mental health outcomes are not the same as wellbeing, there is evidence of moderate nonshared environmental correlations (range = 0.34-0.42) between wellbeing and factors such as depression and internalising symptoms (Bartels et al., 2013; Haworth et al., 2015). This suggests that nonshared environmental factors identified for mental illness are potential nonshared environmental factors for wellbeing. So far, the nonshared environmental factors identified for negative mental health outcomes in adolescence are largely social factors. Parental warmth is moderately associated with behavioural problems (MZ differences correlation = -0.25, Bowes, Maughan, Caspi, Moffitt, & Arseneault, 2010), authoritative parenting is associated with peer problems in childhood ($r = 0.67$, Yamagata et al., 2013), and friendship quality (co-rumination) is somewhat associated with anxiety ($r = 0.20$) and depression ($r = 0.09$, Dirghangi et al., 2015). There is also strong evidence that peer victimisation causally influences negative mental health outcomes. Bullying increases the odds of childhood social anxiety by 1.7 and young adult suicide ideation by 2.9 (Silberg et al., 2016), and also predicts increased anxiety and depression with substantial effects (standardised Beta coefficients 0.27 and 0.37, Singham et al., 2017). Based on findings for poor mental health, recent publications have recommended interventions to reduce symptoms of mental illness and promote positive wellbeing focused on reducing victimisation and improving friendships (Arseneault, 2017; Harmelen et al., 2017). However, it is not yet clear whether peer relationships are a casual mechanism for positive mental health outcomes. In this chapter, we add to this literature by extending the study of these potential nonshared environmental influences in explaining individual differences in positive aspects of mental health.

6.2.1 Potential nonshared environmental factors for adolescent wellbeing

We identified potential nonshared environmental factors by assessing the nonshared environmental factors for mental illness and from observational studies of wellbeing. Associations from observational studies are confounded by genetic influences and environmental effects shared by family members (referred to as shared environment), so nonshared environmental factors may not drive the observed associations. Subjective wellbeing in adolescence is moderately associated with both peer relationships and parental relationships (correlations range 0.36 to 0.41, Oberle, Schonert-Reichl, & Zumbo, 2011), and together relationships with peers and parents explain approximately 22 to 35% of the variance in subjective wellbeing (Yucel & Yuan, 2016). Subjective wellbeing has also been moderately associated with school engagement (average correlation = 0.35, Lewis, Huebner, Malone, & Valois, 2011); and subjective wellbeing has been somewhat associated with the school environment, though the evidence is mixed (for review, see Kidger, Araya, Donovan, & Gunnell, 2012). Peer relationships have long been considered the most likely explanation of nonshared environmental variation in personality and behaviour during adolescence

(Harris, 1998) and explain approximately 62% of the variance in subjective wellbeing in adolescence whilst controlling for the effects of age and gender (Balluerka, Gorostiaga, Alonso-Arbiol, & Aritzeta, 2016). Negative peer experiences, including peer victimisation and bullying, are negatively associated with subjective wellbeing (for review see Arseneault, 2017). Further research is needed to establish whether these factors are specific nonshared environmental influences on both subjective and eudaimonic wellbeing during adolescence and estimate the extent of their impact once genetic and shared environmental influences have been controlled.

Here, our goal was to use an MZ differences design to identify specific nonshared environmental factors as plausible causal mechanisms for wellbeing in adolescence. Based on previous literature we assessed the impact of nonshared environmental factors from four key environmental domains: school engagement, school performance, parent relationships and peer relationships. Though some of these environments (school engagement and school performance) may be considered as behavioural measures, it is important to note that any within-pair discordance must be due to nonshared environmental factors and can be considered as specific nonshared environments (Asbury et al., 2017). Here, my analysis uses our *flourishing* and *aspirational drive* components as well as eight of the traits that loaded onto the *flourishing* component in Chapter 4. I also provide a particular focus on subjective wellbeing because most research uses subjective wellbeing indicators and we feel this would be of most interest to the scientific community. Our previous work has suggested that partly distinct nonshared environmental factors are important for these different measures of wellbeing (Haworth et al., 2015; Wootton, Davis, Mottershaw, Wang, & Haworth, 2017; Chapter 5), so we explored the potential specificity of these nonshared environmental factors across our wellbeing components and our eight wellbeing indicators in adolescence.

6.3 Methods

6.3.1 Participants and measures

Data were collected as part of the Twins Early Development Study, as described in Chapter 3, section 3.1. Here, we used wellbeing data from 10,915 individuals including 5,302 complete twin pairs (1,931 monozygotic and 3,371 dizygotic pairs). We analysed two wellbeing components, eight wellbeing indicators and four environment domains. The four environment domains were derived from 12 measures (seven scales; two with subscales). For a participant's data to be included in the final dataset, the participant must have completed at least 50% of a scale. To be included in the environment domains (which were derived as composites of multiple scales), participants must have data for at least 50% of the scales that constitute the domains.

6.3.1.1 Wellbeing measures

The two wellbeing components were derived as described in the previous two chapters. *Flourishing* was composed of life satisfaction, subjective happiness, relatedness, autonomy, competence, meaning in life, gratitude, trust and optimism. *Aspirational drive* was composed of gratitude, hopefulness, ambition, grit and curiosity. Two wellbeing indicators represented subjective wellbeing: life satisfaction and subjective happiness. Six indicators represented eudaimonic wellbeing. These wellbeing indicators were chosen because of their loadings on our *flourishing* component in Chapter 4. Trust was not included in this analysis as it was measured using a single binary item. The wellbeing indicators were collected across the web and booklet studies. Web measures included life satisfaction, subjective happiness, gratitude, and optimism. Booklet measures included life satisfaction, subjective happiness, relatedness, autonomy, competence and meaning in life. Only web measures of life satisfaction and subjective happiness are presented in the main text as they were collected at the same time as our environment measures. All measures were collected using validated age appropriate scales (see Chapter 3, section 3.1).

6.3.1.2 Environment measures

We wanted to explore the effects of the school environment and social relationships on wellbeing. We chose to organise the school environment into two domains of school engagement and school performance because school engagement is a single measure and semantically different from school performance. Based on previous theory about the influence of parents and peers during adolescence (Harris, 2011), we explored the effects of peer and parent relationships separately. Consequently, the environment measures were categorised into four domains: school engagement, school performance, parent relationships and peer relationships. School engagement consisted of five subscales: teacher-student relations; control/relevance of schoolwork; peer support for learning; future aspirations and goals; and family support for learning. School performance was measured as mean GCSE grade score. Parent Relationships was derived as a composite of four separate scales: parental monitoring, parental control, positive parental discipline and negative parental discipline. Peer relationships was derived as a composite of peer attachment and peer victimisation. Composites were derived by taking a standardised mean score of the responses to each scale, where individuals must have completed at least 50% of the scales to be included. All measures were collected online as part of the web study at age 16 using age-appropriate scales (Table 6.1).

6.3.2 Statistical analyses

All analyses were calculated using MZ twin pairs. First, I calculated the correlations between the environment measures and the wellbeing measures using OpenMx (Neale et al., 2015) in R. This allowed us to control for the effects of age and sex so that the residuals can be interpreted as the expression of the variable at the average age and across girls and boys. Second, I calculated MZ difference scores, which were used for the rest of the analyses.

Within-pair difference scores were calculated by randomly allocating one twin from each twin pair as Twin 1 or Twin 2, then subtracting Twin 2's score from Twin 1's score. Using these MZ difference scores, I first calculated the correlations between the environment domains, individual environment scales and the wellbeing measures to assess whether there was a relationship between our environmental exposures and our wellbeing measures. I then conducted regression analyses using the MZ difference scores. We performed separate linear regressions for each of the four environment domains (school engagement, school performance, parent relationships, and peer relationships) on each of the wellbeing measures (ten in total, with two wellbeing components, two indicators of subjective wellbeing and six indicators of eudaimonic wellbeing). We then performed multiple regressions that included all four environment domains. We calculated the incremental variance explained by each domain, which indicates the independent contribution of each domain beyond the variance explained by the rest of the model.

Table 6.1 Description of the environment measures

Measure	Scale	Reference	Chronbach's Alpha (α)	Number of items; (number of reversed items)	Response scale
School Engagement					
Teacher-Student Relations	School Engagement Instrument[a]	Appleton, Christenson, Kim, & Reschly (2006)	0.91	6	Four-points: 'strongly disagree' to 'strongly agree'
Control/relevance of schoolwork	School Engagement Instrument	Appleton, Christenson, Kim, & Reschly (2006)	0.76	4	Four-points: 'strongly disagree' to 'strongly agree'
Peer support for learning	School Engagement Instrument	Appleton, Christenson, Kim, & Reschly (2006)	0.89	3	Four-points: 'strongly disagree' to 'strongly agree'
Future aspirations and goals	School Engagement Instrument	Appleton, Christenson, Kim, & Reschly (2006)	0.92	3	Four-points: 'strongly disagree' to 'strongly agree'
Family support for learning	School Engagement Instrument	Appleton, Christenson, Kim, & Reschly (2006)	0.95	3	Four-points: 'strongly disagree' to 'strongly agree'
School performance					
Mean GCSE grade score	General Certificate of Secondary Education (GCSE) are compulsory end-of-school assessments in the UK. GCSE scores were collected using a booklet posted to families immediately after the adolescents received their results. At data collection, grades ranged from A* to G. We assigned numerical values to the GCSE scores, ranging from 4 for G to 11 for A* to calculate the mean GCSE score. We used this as an indicator of overall school performance.				

Measure	Scale	Reference	Chronbach's Alpha (α)	Number of items; (number of reversed items)	Response scale
Parent relationships					
Parental monitoring	Parental monitoring scale	NICHD (2005); Maume (2013)	0.86	6	Four-points: 'doesn't know' to 'knows everything'
Parental control[1]	Items from the NICHD early childcare and youth development study	NICHD (2005); Brody et al. (1994)	0.66	8 (8)	Four-points: 'my parent(s) decide' to 'I decide all by myself'
Positive parental discipline	Previously validated semi-structured interview	Deater-Deckard et al. (1998)	0.52	2	Three-points: 'not true' to 'very true'
Negative parental discipline[b]	Previously validated semi-structured interview	Deater-Deckard et al. (1998)	0.23[c]	2 (2)	Three-points: 'not true' to 'very true'
Peer relationships					
Peer attachment	Peer attachment subscale of the inventory of parent and peer attachment	Armsden & Greenberg (1987)	0.93	25 (7)	Five-points: 'almost never or never true' to 'almost always or always true'
Peer victimisation[b]	Multidimensional peer-victimisation scale[d]	Mynard & Joseph, (2000)	0.80	6	Three-points: 'not at all' to 'more than once'

[a] Reduced to 19 items after the initial pilot study due to space constraints.

[b] These scales were reversed scored for inclusion in the composite, so that a higher score indicated a positive outcome.

[c] One item of negative parental discipline ('When I misbehave I am smacked or slapped') was positively skewed, where the majority (93%) of participants responded 'not true'. This is reflected in the reliability estimate.

[d] Due to space constraints, a shortened 6-item version was used.

The proportion of variance explained by each regression model indicates the proportion of the nonshared environmental variance explained. We also calculated the proportion of the total variance explained by the models using estimates of the nonshared environmental influences on each wellbeing measure calculated by subtracting the MZ twin correlations from 1 (as nonshared environmental influences are responsible for within pair differences, see Chapter 3 section 3.2.1 for description of twin modelling). Therefore we provide estimates of the proportion of the nonshared environmental component that is explained by each environment domain, and then we set this within the context of the total variance in the trait by providing the percentage of variance overall explained by these specific non-shared environmental variables.

Finally, I repeated the analysis using the individual environment scales to gain an understanding of which aspects of our four environmental domains may be driving the observed relationships. In line with the analyses for the domains, I calculated linear regressions to predict the effect of each environment scale on each wellbeing measure, then I entered all of the environment scales into a multiple regression model.

6.4 Results

6.4.1 Descriptive statistics and correlations of individual twin scores

Though *t*-tests showed three measures were statistically different across zygosity (Table 6.2), the effect sizes were very small indicating no meaningful differences. This shows that MZ twins are no different from dizygotic (non-identical) twins and supports the assumptions of twin modelling (see Chapter 2, section 2.1.2.2). The MZ twin correlations range from 0.35 to 0.55 for the wellbeing measures, and 0.11 to 0.89 for the environment measures.

6.4.2 MZ differences analyses

First, I assessed the correlations between the environment domains, individual environment scales, and the wellbeing indicators to understand whether regression analyses were appropriate (Table 6.3). The positive correlations between MZ differences in the environment domains of school engagement, parental relationships and peer relationships and MZ differences in wellbeing show that twins with better scores on the environment domains had better wellbeing across all measures. However, the small correlations with school performance indicates that school performance is likely not related to wellbeing in adolescence. The weak correlations between MZ differences in our wellbeing components *flourishing* and *aspirational drive* and MZ differences in the environments suggest that these environments are unlikely to be specific nonshared environmental influences.

To determine the environment domains that are specific nonshared environmental influences on adolescent wellbeing, we ran a series of regression analyses. There is no evidence that the multiple regression models explained variance in *flourishing* (p = 0.35) and little evidence for *aspirational drive* (p = 0.06). For both our wellbeing components, we explained 1.25% of the nonshared environmental variance. However, there is strong evidence (ps < 0.001) that the multiple regression models explained variance in subjective wellbeing (Table 6.4). On average, the models explained 17.66% of the nonshared environmental variance in subjective wellbeing, which amounts to 8.84% of the total variance. The models also explained on average 6.81% of the nonshared environmental variance in eudaimonic wellbeing, amounting to 3.82% of the total variance (see Figure 6.1).

Table 6.2 Number of twins and means (SD), split by zygosity, and the intrapair correlations for MZ twins (95% confidence intervals) for each of the wellbeing and environment measures.

	Number of MZ twins	**MZ twins Mean (SD)**	**Number of DZ twins**	**DZ twins Mean (SD)**	**MZ twin intrapair correlations (95% CIs)**
Wellbeing measures					
*Flourishing**	1335	0.02 (1.02)	2408	-0.01 (0.99)	0.60 (0.56; 0.63)
*Aspirational drive**	1007	0.01 (1.02)	1655	-0.01 (0.99)	0.48 (0.43; 0.53)
Life Satisfaction	2006	4.63 (0.62)	3316	4.60 (0.62)	0.55 (0.50; 0.59)
Subjective Happiness	2010	5.25 (1.15)	3325	5.21 (1.17)	0.39 (0.34; 0.44)
Relatedness	2665	4.83 (0.86)	4837	4.83 (0.84)	0.51 (0.47; 0.55)
Autonomy	2665	3.99 (0.83)	4837	3.97 (0.83)	0.44 (0.40; 0.49)
Competence	2662	4.06 (0.93)	4836	4.03 (0.93)	0.47 (0.42; 0.51)
Gratitude	2009	5.82 (0.83)	3320	5.78 (0.86)	0.41 (0.35; 0.46)
Optimism	1805	3.25 (0.71)	2942	3.22 (0.73)	0.35 (0.29; 0.41)
Meaning in Life	2658	5.13 (1.10)	4827	5.11 (1.08)	0.48 (0.44; 0.52)
Life Satisfaction (booklet)*	3483	5.74 (1.06)	6158	5.68 (1.05)	0.54 (0.51; 0.58)
Subjective Happiness (booklet)*	3483	5.16 (0.95)	6161	5.10 (0.96)	0.40 (0.36; 0.44)
Environment measures					
School Engagement	1897	3.01 (0.69)	3129	3.01 (0.66)	0.13 (0.07; 0.20)
Teacher-Student Relations	1899	2.89 (0.74)	3131	2.93 (0.72)	0.22 (0.15; 0.28)
Control/relevance of schoolwork	1898	2.87 (0.68)	3129	2.84 (0.65)	0.16 (0.10; 0.23)
Peer support for learning	1895	2.89 (0.76)	3125	2.91 (0.75)	0.16 (0.09; 0.22)
Future aspirations and goals	1895	3.29 (0.94)	3125	3.28 (0.93)	0.11 (0.04; 0.17)
Family support for learning	1892	3.25 (0.95)	3125	3.24 (0.92)	0.12 (0.06; 0.19)
School performance					
Mean GCSE grade score	4581	8.87 (1.18)	8161	8.89 (1.19)	0.89

	Number of MZ twins	MZ twins Mean (SD)	Number of DZ twins	DZ twins Mean (SD)	MZ twin intrapair correlations (95% CIs)
					(0.88; 0.90)
Parent relationships	1796	0.01 (0.57)	2924	-0.01 (0.55)	0.49 (0.44; 0.54)
Parental monitoring*	1809	3.10 (0.58)	2940	3.03 (0.59)	0.42 (0.36; 0.47)
Parental control	1816	4.30 (0.52)	2951	4.33 (0.51)	0.50 (0.45; 0.55)
Positive parental discipline	1804	1.11 (0.52)	2939	1.10 (0.54)	0.34 (0.28; 0.40)
Negative parental discipline*	1808	0.67 (0.39)	2940	0.63 (0.37)	0.42 (0.37; 0.48)
Peer relationships	1775	0.03 (0.81)	2889	-0.01 (0.81)	0.55 (0.50; 0.60)
Peer attachment	1784	74.12 (15.06)	2911	74.14 (14.86)	0.50 (0.45; 0.55)
Peer victimisation*	1895	3.31 (3.19)	3124	3.56 (3.23)	0.52 (0.47; 0.57)

Note. Number of twins refers to the number of individuals. The measures reported here are not standardised (except *flourishing* and *aspirational drive*) and use different scales therefore the means are not comparable. The environment domains of parent relationships and peer relationships are composites of the standardised environment measures in each domain. Parental control, negative parental discipline and peer victimisation were reversed scored for analysis, so that a higher score indicated a positive outcome. Asterisk indicates that t-test showed significant difference ($p < 0.05$) between MZ (monozygotic) and DZ (dizygotic) twins. However, the effect sizes for all differences are small. All twins from each twin pair were included in the analyses. The MZ twin intrapair correlations were calculated on OpenMx, controlling for age and sex. The MZ twin correlations can be used to estimate the proportion of variance explained by nonshared environmental influences by subtracting the correlation from 1. These estimates are almost identical to our previous estimates from univariate twin models reported in Chapter 5, Table 5.1.

Table 6.3 Correlations (95% confidence intervals) for MZ differences in the environment measures and MZ differences in wellbeing across the wellbeing indicators.

	Flourishing	*Aspirational drive*	Life satisfaction	Subjective happiness
School Engagement	0.09 (-0.01; 0.19) 404	0.07 (0.00; 0.13) 866	0.16 (0.09; 0.22) 862	0.10 (0.03; 0.16) 867
Teacher-Student Relations	0.05 (-0.05; 0.15) 406	0.07 (0.00; 0.14) 868	0.15 (0.08; 0.21) 864	0.06 (0.00; 0.13) 869
Control/ relevance of schoolwork	0.08 (-0.02; 0.18) 405	0.07 (0.01; 0.14) 867	0.18 (0.11; 0.24) 863	0.10 (0.04; 0.17) 868
Peer support for learning	0.12 (0.02; 0.21) 403	0.06 (-0.01; 0.12) 865	0.20 (0.14; 0.27) 861	0.18 (0.11; 0.24) 866
Future aspirations and goals	0.07 (-0.03; 0.17) 403	0.04 (-0.02; 0.11) 865	0.07 (0.00; 0.13) 861	0.05 (-0.02; 0.11) 866
Family support for learning	0.10 (0.00; 0.19) 401	0.05 (-0.02; 0.11) 862	0.09 (0.03; 0.16) 858	0.07 (0.00; 0.13) 863
School performance: Mean GCSE grade score	0.08 (0.02; 0.14) 1165	0.04 (-0.03; 0.10) 833	0.10 (0.04; 0.17) 830	-0.04 (-0.10; 0.03) 835

	Relatedness	Autonomy	Competence	Gratitude	Optimism	Meaning in life	Life Satisfaction (booklet)	Subjective Happiness (booklet)
School Engagement	0.07 (-0.03; 0.16) 405	0.13 (0.03; 0.22) 405	0.14 (0.04; 0.23) 405	0.10 (0.04; 0.17) 866	0.10 (0.03; 0.17) 829	0.07 (-0.02; 0.17) 401	0.14 (0.07; 0.22) 700	0.10 (0.02; 0.17) 705
Teacher-Student Relations	0.07 (-0.03; 0.17) 407	0.13 (0.03; 0.23) 407	0.12 (0.03; 0.22) 407	0.08 (0.01; 0.14) 868	0.10 (0.03; 0.17) 831	0.03 (-0.07; 0.12) 403	0.13 (0.06; 0.20) 702	0.08 (0.01; 0.15) 707
Control/ relevance of schoolwork	-0.01 (-0.10; 0.09) 406	0.11 (0.01; 0.21) 406	0.12 (0.02; 0.21) 406	0.12 (0.05; 0.18) 867	0.09 (0.02; 0.16) 830	0.06 (-0.04; 0.15) 402	0.11 (0.03; 0.18) 701	0.09 (0.01; 0.16) 706
Peer support for learning	0.17 (0.07; 0.26) 404	0.19 (0.09; 0.28) 404	0.16 (0.07; 0.26) 404	0.10 (0.04; 0.17) 865	0.13 (0.06; 0.19) 828	0.11 (0.01; 0.20) 400	0.21 (0.14; 0.28) 699	0.15 (0.07; 0.22) 704
Future aspirations and goals	0.02 (-0.07; 0.12) 404	0.05 (-0.04; 0.15) 404	0.07 (-0.02; 0.17) 404	0.08 (0.01; 0.14) 865	0.04 (-0.03; 0.11) 828	0.06 (-0.04; 0.16) 400	0.10 (0.02; 0.17) 699	0.06 (-0.02; 0.13) 704
Family support for learning	0.05 (-0.05; 0.14) 402	0.09 (-0.01; 0.18) 402	0.13 (0.03; 0.22) 402	0.08 (0.02; 0.15) 862	0.07 (0.00; 0.14) 825	0.10 (0.00; 0.20) 398	0.12 (0.05; 0.19) 696	0.08 (0.01; 0.16) 701
School performance: Mean GCSE grade score	0.01 (-0.05; 0.07) 1166	0.03 (-0.03; 0.09) 1166	0.11 (0.06; 0.17) 1164	0.07 (0.00; 0.14) 833	0.08 (0.01; 0.15) 763	0.11 (0.05; 0.16) 1159	0.06 (0.01; 0.11) 1522	0.01 (-0.04; 0.06) 1519

	Flourishing	*Aspirational drive*	**Life satisfaction**	**Subjective happiness**
Parent relationships	0.02 (-0.08; 0.12) 391	-0.04 (-0.11; 0.03) 820	0.24 (0.18; 0.31) 816	0.16 (0.10; 0.23) 821
Parental monitoring	0.04 (-0.06; 0.14) 396	0.03 (-0.04; 0.09) 830	0.19 (0.13; 0.26) 826	0.11 (0.04; 0.17) 831
Parental control	-0.01 (-0.11; 0.09) 398	-0.05 (-0.12; 0.02) 835	0.00 (-0.06; 0.07) 831	-0.03 (-0.10; 0.04) 836
Positive parental discipline	0.02 (-0.08; 0.12) 392	-0.02 (-0.09; 0.05) 826	0.23 (0.17; 0.30) 822	0.15 (0.09; 0.22) 827
Negative parental discipline	0.00 (-0.10; 0.10) 394	-0.04 (-0.11; 0.03) 829	0.07 (0.01; 0.14) 825	0.10 (0.04; 0.17) 830
Peer relationships	-0.05 (-0.15; 0.05) 382	-0.03 (-0.10; 0.04) 800	0.45 (0.39; 0.50) 796	0.32 (0.26; 0.38) 801
Peer attachment	0.02 (-0.07; 0.12) 407	0.02 (-0.05; 0.08) 860	0.47 (0.41; 0.52) 805	0.36 (0.30; 0.42) 810
Peer attachment, trust	0.03 (-0.07; 0.13) 384	-0.01 (-0.08; 0.06) 809	0.44 (0.39; 0.50) 805	0.32 (0.25; 0.38) 810
Peer attachment, communication	0.02 (-0.08; 0.12) 383	0.03 (-0.04; 0.10) 809	0.36 (0.30; 0.42) 805	0.28 (0.22; 0.34) 810
Peer attachment, alienation	-0.02 (-0.12; 0.08) 388	0.03 (-0.04; 0.10) 822	0.33 (0.27; 0.39) 818	0.27 (0.21; 0.33) 823
Peer victimisation	-0.09 (-0.18; 0.01) 403	-0.05 (-0.12; 0.01) 861	0.22 (0.15; 0.28) 857	0.13 (0.06; 0.19) 862

	Relatedness	Autonomy	Competence	Gratitude	Optimism	Meaning in life	Life Satisfaction (booklet)	Subjective Happiness (booklet)
Parent relationships	0.09 (-0.01; 0.19) 392	0.12 (0.02; 0.22) 392	0.14 (0.04; 0.23) 392	0.15 (0.08; 0.21) 820	0.11 (0.04; 0.18) 807	0.13 (0.03; 0.23) 389	0.13 (0.06; 0.20) 671	0.13 (0.06; 0.20) 676
Parental monitoring	0.15 (0.06; 0.25) 397	0.12 (0.02; 0.21) 397	0.14 (0.05; 0.24) 397	0.10 (0.03; 0.17) 830	0.10 (0.03; 0.17) 817	0.16 (0.06; 0.25) 394	0.10 (0.03; 0.18) 679	0.09 (0.02; 0.17) 684
Parental control	0.05 (-0.05; 0.14) 399	-0.03 (-0.13; 0.07) 399	0.00 (-0.10; 0.10) 399	0.04 (-0.02; 0.11) 835	-0.06 (-0.13; 0.01) 822	-0.01 (-0.11; 0.09) 396	-0.06 (-0.14; 0.01) 683	-0.05 (-0.13; 0.02) 688
Positive parental discipline	0.04 (-0.06; 0.14) 393	0.07 (-0.03; 0.17) 393	0.10 (0.00; 0.20) 393	0.14 (0.07; 0.21) 826	0.12 (0.05; 0.18) 813	0.09 (0.00; 0.19) 390	0.13 (0.05; 0.20) 675	0.09 (0.02; 0.17) 680
Negative parental discipline	-0.02 (-0.12; 0.08) 395	0.10 (0.00; 0.20) 395	0.04 (-0.06; 0.14) 395	0.02 (-0.04; 0.09) 829	0.07 (0.00; 0.14) 816	0.05 (-0.05; 0.15) 392	0.10 (0.03; 0.17) 678	0.12 (0.05; 0.19) 683
Peer relationships	0.30 (0.21; 0.39) 383	0.25 (0.15; 0.34) 383	0.17 (0.08; 0.27) 383	0.23 (0.16; 0.29) 800	0.28 (0.22; 0.34) 787	0.12 (0.02; 0.22) 380	0.21 (0.14; 0.28) 657	0.24 (0.17; 0.31) 661
Peer attachment	0.39 (0.30; 0.47) 385	0.30 (0.20; 0.38) 385	0.23 (0.14; 0.33) 385	0.28 (0.21; 0.34) 809	0.31 (0.24; 0.37) 796	0.20 (0.11; 0.30) 382	0.27 (0.20; 0.34) 664	0.28 (0.21; 0.35) 668
Peer attachment, trust	0.34 (0.25; 0.43) 385	0.27 (0.17; 0.36) 385	0.19 (0.09; 0.29) 385	0.25 (0.18; 0.31) 809	0.44 (0.39; 0.50) 805	0.32 (0.25; 0.38) 810	0.34 (0.25; 0.43) 385	0.27 (0.17; 0.36) 385
Peer attachment, communication	0.36 (0.27; 0.44) 384	0.21 (0.11; 0.31) 384	0.21 (0.11; 0.30) 384	0.27 (0.21; 0.34) 809	0.36 (0.30; 0.42) 805	0.28 (0.22; 0.34) 810	0.36 (0.27; 0.44) 384	0.21 (0.11; 0.31) 384
Peer attachment, alienation	0.28 (0.18; 0.37) 389	0.28 (0.18; 0.37) 389	0.21 (0.11; 0.30) 389	0.14 (0.07; 0.21) 822	0.33 (0.27; 0.39) 818	0.27 (0.21; 0.33) 823	0.28 (0.18; 0.37) 389	0.28 (0.18; 0.37) 389
Peer victimisation	0.05 (-0.05; 0.15) 404	0.09 (-0.01; 0.18) 404	0.02 (-0.07; 0.12) 404	0.07 (0.00; 0.13) 861	0.12 (0.05; 0.18) 824	0.00 (-0.10; 0.10) 400	0.07 (0.00; 0.15) 696	0.09 (0.02; 0.17) 700

Note. N = number of complete MZ twin pairs, 380 to 1166.

We explain more variance in subjective wellbeing using the web measures of subjective wellbeing (17.66% of NSE variance) compared to the booklet measures (6.54 % of NSE variance). As our environmental measures were collected on the web, we would expect this pattern. Based on these findings, we may expect to explain lower proportions of variance in the eudaimonic indicators collected on the booklet than the web. However, apart from meaning in life, we explained similar proportions of variance in the eudaimonic indicators measured on the booklet (mean NSE variance = 7.32%) and the web (mean = 7.55%).

As shown in Figure 6.1, peer relationships explained the most variance in both subjective wellbeing and eudaimonic beyond the rest of the model (subjective wellbeing = 12%; eudaimonic wellbeing = 4.22%), followed by parent relationships (subjective wellbeing = 1.84%; eudaimonic wellbeing = 0.81%). In contrast, the school environment domains were less important (see Table 6.4). Peer relationships also explained more variance than parent relationships. These findings indicate that peer relationships are more likely to causally influence adolescent wellbeing than school engagement, school performance and parent relationships.

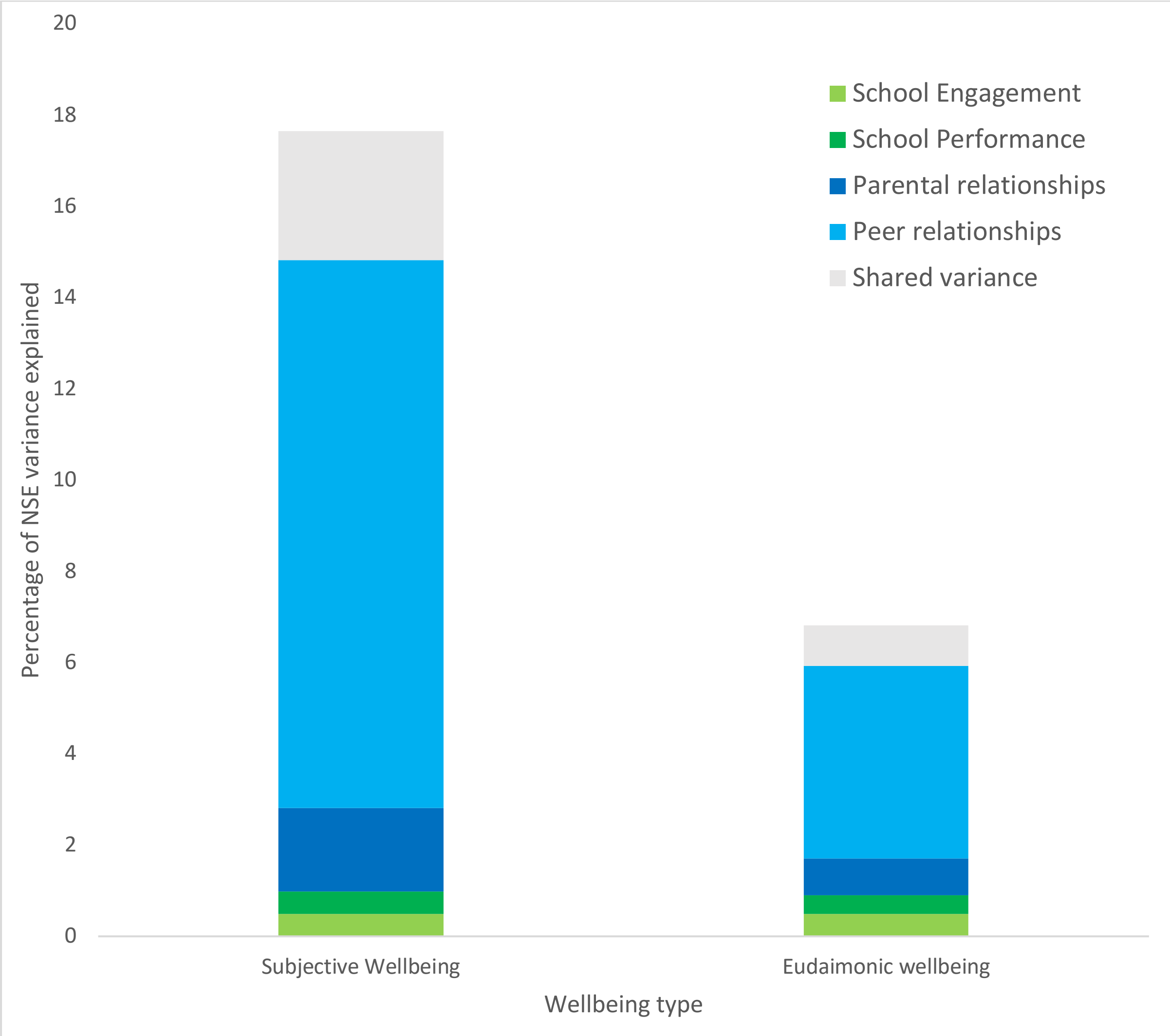


Figure 6.1 Percentage of nonshared environmental variance explained in subjective wellbeing and eudaimonic wellbeing, predicted from a multiple regression model of all environment composites. Each section of the bar indicates the proportion of the variance explained by each environment composite (calculated as the incremental R^2), and the shared variance explained by combining all the environment composites in the model (named shared variance; displayed in grey).

Table 6.4 Summary of multiple regression analyses predicting MZ wellbeing discordance from composites of MZ environment discordance, presented with R^2 from single regression analyses, and the incremental R^2 for each environment.

Environment	Flourishing				Aspirational drive			
	β	*t (p-value)*	Single R^2	Incremental R^2	β	*t (p-value)*	Single R^2	Incremental R^2
School Engagement	0.12	1.41 (0.16)	0.64	0.56	0.11	2.19 (0.03)	0.57	0.67
School Performance	0.05	0.85 (0.40)	0.24	0.20	0.00	0.12 (0.91)	0.01	0.00
Parent relationships	0.01	0.05 (0.96)	0.00	0.00	-0.15	-1.74 (0.081)	0.38	0.43
Peer relationships	-0.15	-1.19 (0.23)	0.44	0.40	-0.09	-1.20 (0.23)	0.24	0.20
	Total Variance Explained in NSE = 1.25%				Total Variance Explained in NSE = 1.25%			
	Total Variance Explained = 0.030%				Total Variance Explained = 0.024%			
	$F(4, 347) = 1.10$				$F(4, 705) = 2.23$			
	$p = 0.3565$				$p = 0.0637$			
	N = 352				N = 710			

Table 6.4 (Continued) Summary of multiple regression analyses predicting MZ wellbeing discordance from composites of MZ environment discordance, presented with R2 from single regression analyses, and the incremental R2 for each environment.

Environment	Life Satisfaction				Subjective Happiness			
	β	*t (p-value)*	Single R^2	Incremental R^2	β	*t (p-value)*	Single R^2	Incremental R^2
School Engagement	0.10	2.45 (0.0147)	2.02	0.66	0.08	1.59 (0.1117)	0.82	0.32
School Performance	0.09	2.68 (0.0075)	1.13	0.79	-0.05	-1.26 (0.2094)	0.10	0.20
Parent relationships	0.36	4.90 (1.222×10^{-6})	5.68	2.62	0.25	2.88 (0.0041)	2.47	1.05
Peer relationships	0.75	12.08 (1.275×10^{-30})	19.75	15.98	0.58	7.94 (8.191×10^{-15})	9.54	8.02
	Total Variance Explained in NSE= 24.11%				Total Variance Explained in NSE= 11.20%			
	Total Variance Explained= 10.85%				Total Variance Explained= 6.83%			
	$F(4,693)= 55.04$				$F(4,698)= 22.01$			
	$p= 2.584\times10^{-40}$				$p= 3.997\times10^{-17}$			
	N= 698				N= 703			
	Relatedness				Autonomy			
	β	*t (p-value)*	Single R^2	Incremental R^2	β	*t (p-value)*	Single R^2	Incremental R^2
School Engagement	0.03	0.56 (0.5758)	0.20	0.08	0.09	1.33 (0.1843)	0.76	0.48
School Performance	0.00	-0.06 (0.9513)	0.02	0.00	0.02	0.37 (0.7146)	0.11	0.04
Parent relationships	0.13	1.23 (0.2203)	0.99	0.40	0.25	2.09 (0.0374)	2.01	1.18
Peer relationships	0.50	5.32 (1.855×10^{-07})	8.20	7.56	0.47	4.42 (1.322×10^{-05})	6.18	5.26
	Total Variance Explained in NSE= 8.71%				Total Variance Explained in NSE= 7.97%			
	Total Variance Explained= 4.27%				Total Variance Explained= 4.46%			
	$F(4,342)= 8.16$				$F(4,342)= 7.41$			
	$p = 2.710\times10^{-06}$				$p = 9.881\times10^{-06}$			
	N= 347				N= 347			

Table 6.4 (Continued) Summary of multiple regression analyses predicting MZ wellbeing discordance from composites of MZ environment discordance, presented with R2 from single regression analyses, and the incremental R2 for each environment.

	Competence				Gratitude			
	β	*t (p-value)*	Single R^2	Incremental R^2	*β*	*t (p-value)*	Single R^2	Incremental R^2
School Engagement	0.15	2.14 (0.0331)	1.62	1.27	0.09	1.83 (0.0679)	0.98	0.45
School Performance	0.04	0.66 (0.5080)	0.22	0.12	0.06	1.52 (0.1278)	0.43	0.31
Parent relationships	0.22	1.78 (0.0753)	1.45	0.88	0.29	3.29 (0.0011)	2.48	1.45
Peer relationships	0.31	2.84 (0.0048)	2.85	2.24	0.34	4.69 ($3.307x10^{-06}$)	4.11	2.95
	Total Variance Explained in NSE= 5.29%				Total Variance Explained in NSE= 6.51%			
	Total Variance Explained= 2.80%				Total Variance Explained= 3.84%			
	$F(4,342)= 4.78$				$F(4,697)= 12.13$			
	$p= 0.0009$				$p= 1.545x10^{-09}$			
	N= 347				N= 702			
	Optimism				Meaning in Life			
	β	*t (p-value)*	Single R^2	Incremental R^2	*β*	*t (p-value)*	Single R^2	Incremental R^2
School Engagement	0.07	1.45 (0.1464)	0.73	0.28	0.09	1.14 (0.2538)	0.60	0.37
School Performance	0.06	1.48 (0.1398)	0.43	0.29	0.14	2.44 (0.0151)	1.84	1.69
Parent relationships	0.11	1.31 (0.1900)	0.89	0.23	0.20	1.57 (0.1177)	0.91	0.70
Peer relationships	0.51	7.10 ($3.099x10^{-12}$)	7.70	6.71	0.17	1.46 (0.1452)	0.95	0.60
	Total Variance Explained in NSE= 8.58%				Total Variance Explained in NSE= 3.82%			
	Total Variance Explained= 5.58%				Total Variance Explained= 1.99%			
	$F(4,687)= 16.11$				$F(4,339)= 3.36$			
	$p = 1.275x10^{-12}$				$p = 0.0102$			
	N= 692				N= 344			

Table 6.4 (Continued) Summary of multiple regression analyses predicting MZ wellbeing discordance from composites of MZ environment discordance, presented with R2 from single regression analyses, and the incremental R2 for each environment.

Environment	Life Satisfaction (booklet)				Subjective Happiness (booklet)			
	β	*t (p-value)*	Single R^2	Incremental R^2	β	*t (p-value)*	Single R^2	Incremental R^2
School Engagement	0.10	1.96 (0.0501)	1.18	0.62	0.09	1.62 (0.1048)	0.89	0.42
School Performance	-0.02	-0.43 (0.6705)	0.00	0.03	-0.06	-1.48 (0.1403)	0.19	0.34
Parent relationships	0.24	2.61 (0.0092)	1.99	1.10	0.24	2.35 (0.0193)	1.80	0.87
Peer relationships	0.34	4.36 (1.566×10^{-05})	4.03	3.04	0.46	5.32 (1.510×10^{-07})	5.47	4.45
	Total Variance Explained in NSE = 5.93%				Total Variance Explained in NSE = 7.15%			
	Total Variance Explained = 2.73%				Total Variance Explained = 4.29%			
	$F(4, 587) = 9.24$				$F(4, 590) = 11.37$			
	$p = 3.005 \times 10^{-07}$				$p = 6.820 \times 10^{-09}$			
	N = 592				N = 595			

Note. All variables are based on twin difference scores. Beta coefficients are standardised. N= number of complete MZ pairs, which ranges 344 to 703 as we only included individuals with complete data and wellbeing indicators from the booklet required individuals to have completed both forms of data collection. The multiple regression statistics are the standardised Betas, *t*-values (*p*-value), total percentage of variance explained, *F*-statistic (with *p*-value). Only the R^2 from the single regressions is reported (Single R^2). The incremental R^2 is calculated by subtracting a reduced model (with the environment of interest removed) from the full model. NSE = nonshared environmental influences. *Total variance explained in NSE* is calculated as the proportion of nonshared environmental variance explained by the model. *Total variance explained* is calculated as the proportion of the total variance of the wellbeing indicator explained by the model.

6.4.3 Additional analyses: the effect of peer relationships on wellbeing in adolescence

We repeated the above analyses using the individual environment scales to understand which factors are driving the relationship between the environment domains and the wellbeing indicators (Table 6.5). As neither model of *flourishing* or *aspirational drive* significantly explained nonshared environmental variance, we concentrated on our subjective and eudaimonic wellbeing indicators. Given the importance of peer relationships identified above, we were particularly interested to explore whether a specific aspect of peer relationships was driving the effect. Analysis of the separate peer relationship scales (attachment and victimisation) indicated that the effect of peers was driven by peer attachment, which explained on average 9.69% of the nonshared environmental variance in subjective wellbeing and 4.58% in eudaimonic wellbeing compared to just 0.97% and 0.14% of the nonshared environmental variance explained by peer victimisation. These findings indicate peer attachment is driving the association between peer relationships and wellbeing in adolescence.

Table 6.5 Summary of multiple regression analyses predicting MZ wellbeing discordance from MZ environment discordance, with all environment scales in the same model, grouped by environment type. Presented with R^2 from single regression analyses, and the incremental R^2 for each environment.

Environment	Life Satisfaction				Subjective Happiness			
	β	*t (p-value)*	Single R^2	Incremental R^2	β	*t (p-value)*	Single R^2	Incremental R^2
Total School Engagement			6.06	1.78			4.62	1.68
Teacher-Student Relations	0.00	-0.03 (0.9770)	1.84	0.00	-0.11	-1.81 (0.0711)	0.25	0.40
Control/relevance of schoolwork	0.16	3.18 (0.0015)	2.56	1.04	0.09	1.53 (0.1260)	0.77	0.29
Peer support for learning	0.07	1.43 (0.1536)	3.64	0.21	0.16	2.91 (0.0037)	2.82	1.04
Future aspirations and goals	-0.11	-1.71 (0.0884)	0.43	0.30	-0.12	-1.58 (0.1145)	0.13	0.31
Family support for learning	-0.02	-0.36 (0.7196)	0.57	0.01	0.05	0.65 (0.5166)	0.34	0.05
School performance: Mean GCSE grade score	0.08	2.43 (0.0154)	1.13	0.61	-0.04	-1.13 (0.2588)	0.10	0.16
Parent Relationships			7.68	2.62			4.19	1.10
Parental monitoring	0.07	2.04 (0.0413)	3.87	0.43	0.04	1.09 (0.2777)	1.90	0.14
Parental control	0.04	1.46 (0.1435)	0.06	0.22	-0.01	-0.27 (0.7836)	0.14	0.01
Positive parental discipline	0.11	3.69 (0.0002)	5.38	1.40	0.08	2.27 (0.0238)	2.41	0.63
Negative parental discipline	0.02	0.59 (0.5561)	0.32	0.04	0.04	1.11 (0.2688)	0.66	0.15
Peer Relationships			23.88	15.97			12.37	7.88
Peer attachment	0.37	11.11 (1.769×10^{-26})	22.18	12.73	0.29	7.38 (4.682×10^{-13})	11.89	6.65
Peer victimisation	0.12	3.78 (0.0002)	4.77	1.47	0.07	1.95 (0.0511)	1.82	0.47
	Total Variance Explained in NSE = 29.34%				Total Variance Explained in NSE = 15.68%			
	Total Variance Explained = 13.20%				Total Variance Explained = 9.88%			
	$F(12, 685) = 23.70$				$F(12, 690) = 10.69$			
	$p = 2.030 \times 10^{-44}$				$p = 1.228 \times 10^{-19}$			
	N = 698				N = 703			

Table 6.5 (continued) Summary of multiple regression analyses predicting MZ wellbeing discordance from MZ environment discordance, with all environment scales in the same model, grouped by environment type. Presented with R^2 from single regression analyses, and the incremental R^2 for each environment.

Environment	Relatedness				Autonomy			
	β	*t (p-value)*	Single R^2	Incremental R^2	*β*	*t (p-value)*	Single R^2	Incremental R^2
Total School Engagement			7.05	3.65			3.82	1.40
Teacher-Student Relations	0.00	0.05 (0.9564)	0.10	0.00	0.04	0.46 (0.6427)	0.61	0.06
Control/relevance of schoolwork	-0.16	-2.25 (0.0249)	0.13	1.22	0.02	0.20 (0.8407)	0.45	0.01
Peer support for learning	0.20	3.00 (0.0029)	2.88	2.17	0.13	1.67 (0.0953)	2.27	0.74
Future aspirations and goals	-0.14	-1.39 (0.1652)	0.00	0.47	-0.17	-1.53 (0.1278)	0.07	0.62
Family support for learning	0.11	1.21 (0.2274)	0.12	0.35	0.07	0.62 (0.5376)	0.37	0.10
School performance: Mean GCSE grade score	-0.02	-0.47 (0.6411)	0.02	0.05	0.02	0.30 (0.7677)	0.11	0.02
Parent Relationships			2.86	2.03			4.35	1.99
Parental monitoring	0.10	1.99 (0.0471)	2.39	0.96	0.13	2.23 (0.0261)	3.37	1.32
Parental control	0.07	1.52 (0.1283)	0.16	0.56	-0.02	-0.38 (0.7028)	0.15	0.04
Positive parental discipline	-0.02	-0.40 (0.6915)	0.55	0.04	0.02	0.42 (0.6737)	0.95	0.05
Negative parental discipline	-0.06	-1.35 (0.1792)	0.20	0.44	0.06	1.09 (0.2776)	0.62	0.31
Peer Relationships			14.11	9.16			8.19	4.13
Peer attachment	0.31	6.15 (2.265×10^{-09})	14.10	9.10	0.22	3.75 (0.0002)	7.96	3.71
Peer victimisation	-0.02	-0.42 (0.6739)	0.43	0.04	0.04	0.70 (0.4831)	1.02	0.13
	Total Variance Explained in NSE = 19.50%				Total Variance Explained in NSE = 15.68%			
	Total Variance Explained = 9.46%				Total Variance Explained = 8.78%			
	$F(12, 334) = 6.74$				$F(12, 334) = 3.72$			
	$p = 7.059 \times 10^{-11}$				$p = 2.673 \times 10^{-05}$			
	N = 347				N = 347			

Table 6.5 (continued) Summary of multiple regression analyses predicting MZ wellbeing discordance from MZ environment discordance, with all environment scales in the same model, grouped by environment type. Presented with R^2 from single regression analyses, and the incremental R^2 for each environment.

Environment	Competence				Gratitude			
	β	*t (p-value)*	Single R^2	Incremental R^2	β	*t (p-value)*	Single R^2	Incremental R^2
Total School Engagement			4.23	3.31			1.72	1.01
Teacher-Student Relations	-0.04	-0.43 (0.6666)	0.72	0.05	-0.09	-1.49 (0.1357)	0.37	0.29
Control/relevance of schoolwork	0.04	0.49 (0.6257)	1.10	0.06	0.12	1.97 (0.0488)	1.31	0.51
Peer support for learning	0.15	1.85 (0.0648)	3.11	0.92	-0.01	-0.18 (0.8551)	1.03	0.00
Future aspirations and goals	-0.27	-2.32 (0.0210)	0.39	1.44	0.06	0.73 (0.4674)	0.70	0.07
Family support for learning	0.25	2.21 (0.0276)	1.68	1.31	-0.01	-0.16 (0.8710)	0.58	0.00
School performance: Mean GCSE grade score	0.03	0.52 (0.6008)	0.22	0.07	0.05	1.24 (0.2172)	0.43	0.20
Parent Relationships			2.86	1.17			3.37	1.70
Parental monitoring	0.09	1.54 (0.1252)	2.26	0.63	0.05	1.31 (0.1923)	1.59	0.22
Parental control	0.01	0.15 (0.8813)	0.00	0.01	0.06	1.55 (0.1219)	0.20	0.31
Positive parental discipline	0.05	0.92 (0.3564)	1.25	0.23	0.09	2.51 (0.0123)	2.42	0.82
Negative parental discipline	-0.01	-0.25 (0.8027)	0.02	0.02	-0.01	-0.25 (0.8042)	0.01	0.01
Peer Relationships			5.76	2.84			7.16	5.17
Peer attachment	0.20	3.26 (0.0012)	5.70	2.84	0.25	6.21 (8.987×10^{-10})	7.16	5.03
Peer victimisation	-0.03	-0.45 (0.6562)	0.05	0.05	0.00	0.03 (0.9784)	0.23	0.00
	Total Variance Explained in NSE = 10.64%				Total Variance Explained in NSE = 10.24%			
	Total Variance Explained = 5.85%				Total Variance Explained = 6.14%			
	$F(12, 334) = 3.31$				$F(12, 689) = 6.55$			
	$p = 0.0001$				$p = 3.694 \times 10^{-11}$			
	N = 347				N = 702			

Table 6.5 (continued) Summary of multiple regression analyses predicting MZ wellbeing discordance from MZ environment discordance, with all environment scales in the same model, grouped by environment type. Presented with R^2 from single regression analyses, and the incremental R^2 for each environment.

Environment	Optimism				Meaning in Life			
	β	*t (p-value)*	Single R^2	Incremental R^2	β	*t (p-value)*	Single R^2	Incremental R^2
Total School Engagement			1.99	0.60			2.24	2.56
Teacher-Student Relations	0.03	0.45 (0.6496)	0.74	0.03	-0.17	-1.82 (0.07013)	0.00	0.91
Control/relevance of schoolwork	0.05	0.83 (0.4092)	0.66	0.09	-0.02	-0.18 (0.8600)	0.24	0.01
Peer support for learning	0.02	0.40 (0.6921)	1.26	0.02	0.10	1.23 (0.2191)	1.36	0.42
Future aspirations and goals	-0.13	-1.66 (0.0983)	0.13	0.36	-0.13	-1.07 (0.2869)	0.31	0.31
Family support for learning	0.08	1.10 (0.272)	0.38	0.16	0.25	2.20 (0.0285)	1.16	1.34
School performance: Mean GCSE grade score	0.06	1.54 (0.123)	0.43	0.31	0.13	2.35 (0.0195)	1.84	1.52
Parent Relationships			2.95	0.92			2.06	1.12
Parental monitoring	0.03	0.81 (0.415)	1.14	0.09	0.09	1.48 (0.1391)	1.56	0.61
Parental control	-0.06	-1.67 (0.0951)	0.58	0.36	-0.01	-0.22 (0.8262)	0.02	0.01
Positive parental discipline	0.06	1.63 (0.1035)	1.49	0.35	0.06	0.96 (0.3368)	0.89	0.26
Negative parental discipline	0.02	0.66 (0.5100)	0.26	0.06	-0.01	-0.17 (0.8631)	0.01	0.01
Peer Relationships			9.62	6.57			3.19	1.40
Peer attachment	0.26	6.45 (2.078×10^{-10})	9.08	5.43	0.14	2.21 (0.0277)	2.89	1.35
Peer victimisation	0.07	1.91 (0.0560)	1.66	0.48	-0.05	-0.76 (0.4482)	0.04	0.16
	Total Variance Explained in NSE = 11.51%				Total Variance Explained in NSE = 8.52%			
	Total Variance Explained = 7.25%				Total Variance Explained = 4.60%			
	$F(12, 679) = 7.36$				$F(12, 331) = 2.57$			
	$p = 8.363 \times 10^{-13}$				$p = 0.0029$			
	N = 692				N = 344			

Table 6.5 (continued) Summary of multiple regression analyses predicting MZ wellbeing discordance from MZ environment discordance, with all environment scales in the same model, grouped by environment type. Presented with R^2 from single regression analyses, and the incremental R^2 for each environment.

Environment	Life Satisfaction (booklet)				Subjective Happiness (booklet)			
	β	*t (p-value)*	Single R^2	Incremental R^2	β	*t (p-value)*	Single R^2	Incremental R^2
Total School Engagement			4.32	1.91			2.91	0.79
Teacher-Student Relations	0.01	0.14 (0.8885)	0.81	0.00	-0.03	-0.42 (0.6772)	0.47	0.03
Control/relevance of schoolwork	-0.06	-0.98 (0.3269)	0.40	0.15	0.03	0.51 (0.6136)	0.67	0.04
Peer support for learning	0.18	3.08 (0.0021)	3.31	1.46	0.12	1.86 (0.0640)	2.19	0.53
Future aspirations and goals	-0.08	-1.02 (0.3086)	0.42	0.16	-0.08	-0.85 (0.3945)	0.29	0.11
Family support for learning	0.04	0.46 (0.6477)	0.69	0.03	0.02	0.25 (0.8024)	0.45	0.01
School performance: Mean GCSE grade score	-0.01	-0.22 (0.8249)	0.00	0.01	-0.06	-1.34 (0.1796)	0.19	0.28
Parent Relationships			4.16	1.88			3.20	1.17
Parental monitoring	0.05	1.23 (0.2194)	1.56	0.23	0.02	0.50 (0.6165)	0.96	0.04
Parental control	-0.02	-0.61 (0.5454)	0.24	0.06	0.00	-0.05 (0.9619)	0.14	0.00
Positive parental discipline	0.11	2.79 (0.0054)	2.79	1.20	0.07	1.51 (0.1319)	1.31	0.35
Negative parental discipline	0.04	0.92 (0.3556)	0.33	0.13	0.10	2.18 (0.0300)	1.26	0.73
Peer Relationships			6.96	3.26			7.88	4.88
Peer attachment	0.19	4.60 (5.203×10^{-06})	6.95	3.25	0.26	5.48 (6.494×10^{-08})	7.80	4.62
Peer victimisation	-0.02	-0.53 (0.5941)	0.20	0.04	0.02	0.53 (0.5950)	0.62	0.04
	Total Variance Explained in NSE = 10.92%				Total Variance Explained in NSE = 10.41%			
	Total Variance Explained = 5.02%				Total Variance Explained = 6.14%			
	F(12, 579) = 7.36				F(12, 582) = 5.64			
	$p = 9.197 \times 10^{-10}$				$p = 3.349 \times 10^{-09}$			
	N = 592				N = 595			

Note. All variables are based on twin difference scores. Beta coefficients are standardised. N = number of complete MZ pairs, 344 to 703. The multiple regression statistics are the standardised Betas, *t*-values (*p*-value), total percentage of variance explained, *F*-statistic (with *p*-value). Only the R^2 from the single regressions is reported (Single R^2). The incremental R^2 is calculated by subtracting a reduced model (with the environment of interest removed) from the full model. NSE = nonshared environmental influences. *Total variance explained in NSE* is calculated as the proportion of nonshared environmental variance explained by the model. Total variance explained is calculated as the proportion of the total variance of the wellbeing indicator explained by the model.

6.5 Discussion

Using an MZ twin differences design, we were able to identify specific environment domains that effect adolescent wellbeing using both subjective and eudaimonic wellbeing indicators. We did not identify specific environmental influences on our *flourishing* and *aspirational drive* components. Despite this, our findings demonstrate the ability to explain substantial proportions of variance using nonshared environmental indicators. Specifically, our findings show the importance of peer relationships to subjective and eudaimonic wellbeing in adolescence in comparison to our other environment domains of parent relationships, school engagement and school performance.

6.5.1 Explaining substantial proportions of variance

Specific environmental factors usually explain small proportions (median approximately 3%) of the total variance in behavioural traits (Davey Smith, 2011; Turkheimer & Waldron, 2000). So far, common genetic variants have only explained approximately 6% of the variance in subjective wellbeing (Baselmans & Bartels, 2018). Here, we explain larger proportions: up to 11% of the total variance in life satisfaction and 7% of subjective happiness. The MZ differences design uses observed within-pair differences as a predictor to estimate observed within-pair differences in an outcome, controlling for genetic and shared environmental confounding. This is the closest observational approach to infer causality because the co-twin with less exposure to a predictor acts as a control for the co-twin with greater exposure (Singham et al., 2017). The specific nonshared environmental factors identified can lead to plausible hypotheses for potential causal mechanisms and effective interventions. Arguably, they are more immediately valuable than specific genetic variants that indicate potential causal pathways because we are often unsure of the biological mechanisms that drive the genetic associations or how we can intervene.

We explain a substantial proportion of the nonshared environmental influences on wellbeing, with an average of 17.66% of the subjective wellbeing indicators and 6.81% of the eudaimonic wellbeing indicators. This is greater than MZ differences studies of psychopathology and negative mental health outcomes, which have explained up to 6% (Liang & Eley, 2005) and up to 12% using extreme discordant twin samples (Asbury, Dunn, & Plomin, 2006). Our findings demonstrate that the effort to identify specific nonshared environmental factors is not such a 'gloomy prospect' (Turkheimer & Waldron, 2000). However, we did not significantly explain any variation in MZ differences for our wellbeing components of *flourishing* and *aspirational drive*. This may be because the environments we measured are phenotypically associated with *flourishing* and *aspirational drive* due to genetic influences, and may be because there are other specific nonshared environmental influences on these components. There is also a large proportion of the nonshared environment (more than 75%) that remains unexplained in our subjective and eudaimonic wellbeing indicators. This may be due to unsystematic nonshared environmental influences, such as accidents, chance events and other life events that are difficult to capture in large scale data collection (Davey Smith, 2011). It also could be due to measurement error, which is modelled as part of the nonshared environmental estimates in the twin design.

To address the large proportion of unexplained nonshared environmental influences, we first need more investment to design better ways to measure the environment and capture unsystematic nonshared environmental influences such as accidents and chance events, though this may be as difficult as identifying rare variant differences in genetics, which are not captured by standard genotyping (Zhu et al., 2015). One approach may be to capture more dynamic measures of the environment, such as through smartphone apps or smartwatches that collect a range of health and activity data (Hartman, Nelson, & Weiner, 2018; Skinner, Stone, Doughty, & Munafò, 2018). Using such dynamic measures of individual interactions with the environment will enable us to advance our understanding of specific environmental influences. Second, we should aim towards reducing measurement error, which likely accounts for at least a small proportion of the unexplained nonshared environmental influences. It is an issue with self-reports of behavioural traits that we can never be sure whether we are measuring the true level of the trait. More validation of self-report measures, the use of alternative measures and triangulation of data would increase our ability to estimate and reduce measurement error. Research now uses experience sampling, implicit measures of social media and physiological measures to address these issues (Diener, Scollon, & Lucas, 2003; Kahneman, Krueger, Schkade, Schwarz, & Stone, 2004; Settanni & Marengo, 2015). It will be exciting to see the path taken by the next decade of research with more focus on environmental influences.

6.5.2 Specificity in the nonshared environmental influences across subjective and eudaimonic wellbeing indicators

Using our environment predictors, we were better able to explain variance in subjective wellbeing compared to eudaimonic wellbeing. For example, we explained almost three times as much nonshared environmental variance in subjective wellbeing (mean = 17.66%) compared to eudaimonic wellbeing (mean = 6.81%), and almost twice as much total variance (subjective wellbeing = 6.81%; eudaimonic wellbeing = 3.82%). It is plausible that these findings are due to the time of data collection, where subjective wellbeing was captured contemporaneously with our environment measures whereas four eudaimonic indicators were captured approximately six months later. Using the booklet measures of subjective wellbeing, we explain approximately 4% of the total variance, which is more comparable with eudaimonic wellbeing (3.82%). This indicates that the impact of environments on wellbeing decreases across time and consistently positive environments may be key to maintaining wellbeing in adolescence.

Across the eudaimonic wellbeing indicators, we explain similar proportions of variance regardless of time of data collection. The exception is meaning in life, where it was measured later and we explain less variance. Without the same eudaimonic traits measured on both forms of data collection, it is difficult to draw firm conclusions. It is possible that our environments have a larger or more lasting impact on the eudaimonic traits measured on the booklet (relatedness, autonomy and competence) than the web (gratitude and optimism). This may be because the environments we measured are more important to relatedness, autonomy and competence compared to gratitude and optimism, or because gratitude and optimism are influenced by a greater range of environments. We need further research that explores the environments important to eudaimonic traits to really understand this complex relationship.

We also observe differences in the magnitude of effect across subjective wellbeing and eudaimonic wellbeing, which we expected based on the modest nonshared environmental correlations between the wellbeing indicators in Chapter 5. For example, though peer relationships explain a significant amount of variance in each wellbeing indicator except meaning in life, we explain much more variance in life satisfaction (15.98%) compared to gratitude (2.95%). Furthermore, meaning in life shows different patterns to the other wellbeing indicators because only school performance explains any variance. It is concerning that at 16, adolescents are seeking their meaning through school performance. It could be that adolescents perceive their exams at the end of compulsory education as pivotal in their life (Denscombe, 2000), and we therefore need to support adolescents in attaining meaning from other aspects of their lives. However, school performance only explains 1.69% of the variance in meaning in life above and beyond the rest of the model. It is plausible that adolescents achieve meaning through other aspects of their environment which we have not measured. We need to explore a wider range of environments to uncover exactly which environments are important to subjective and eudaimonic wellbeing in adolescence.

6.5.3 The importance of peer relationships to wellbeing in adolescence

Our findings show that peer relationships explain substantial proportions of variance in subjective and eudaimonic wellbeing in adolescence and support previous exploratory research (Asbury et al., 2017). Positive peer relationships are therefore a good candidate for further investigation of causal mechanisms for wellbeing and for wellbeing interventions, supporting suggestions from recent mental health and bullying research (Arseneault, 2017; Harmelen et al., 2017). However, wellbeing is such an important variable beyond the absence of mental illness that we should also explore interventions that are specific to wellbeing, and which could be delivered in a universal approach, rather than a targeted approach that can be stigmatising. Some effective wellbeing interventions from the literature do aim to improve current social relationships (Layous, Chancellor, Lyubomirsky, Wang, & Doraiswamy, 2011), and one randomised control trial found interventions focused on prosocial behaviours increase relationship satisfaction and happiness compared to self-focused activities (O'Connell, O'Shea, & Gallagher, 2016). Yet a lack of methodologically rigorous studies such as randomised controlled trials means that the interpretation of positive psychological interventions is so far limited (Bolier et al., 2013). We propose that future research should use robust methods to explore the direct impact of interventions that improve adolescent friendships to target wellbeing, ideally using randomised control trials or a co-twin control design to account for genetic and shared environmental influences. Interventions to improve adolescent friendships may be best focused on activities that build opportunities for collaboration and teamwork.

6.5.4 Limitations

Our findings may be caused by bidirectional influences, where pre-existing levels of wellbeing due to nonshared environmental factors affected the current reporting of peer relationships. Longitudinal studies show a bidirectional relationship is plausible (Martin, Huebner, & Valois, 2008; Workum, Scholte, Cillessen, Lodder, & Giletta, 2013), though they have not controlled for genetic or shared environmental influences. This could be addressed using a longitudinal MZ differences design or a co-twin control intervention as described above.

Additionally, our findings could be due to shared measurement error across the wellbeing and environment measures. The lower proportion of variance explained on the booklet compared to the web measures of subjective wellbeing may indicate the presence of measurement error. There was on average six months between data collection types, which suggests the impact of peer relationships reduces over time. It is plausible that consistently good peer relationships are required for adolescent wellbeing, which supports evidence that nonshared environmental influences on wellbeing are largely time-specific (Nes, Røysamb, Tambs, Harris, & Reichborn-Kjennerud, 2006). This emphasises the problem with investigating environmental influences compared to genetic influences, which are more stable over time (Nes et al., 2006). However, it also highlights that environmental influences are potentially more malleable and present more opportunity for changing behaviour. Most previous MZ differences studies are longitudinal (Liang & Eley, 2005; Singham et al., 2017), which could explain the lower proportion of variance explained in comparison with our findings. However, we explained approximately 4% of the total variance in the booklet measures of subjective wellbeing, which is still substantial, and indicates that our findings are not all driven by contemporaneous data collection.

Finally, our analyses were limited by the number of environments we measured. We chose to measure environments that have been associated with wellbeing in exploratory research (Asbury et al., 2017) or observational research that did not control for genetic confounding (Balluerka et al., 2016; Lewis et al., 2011; Oberle et al., 2011). Though we explained substantial proportions of the nonshared environmental variance, a large proportion remained unexplained. It is likely there are many environments that are associated with wellbeing in adolescence and we need to explore a range of environments to explain larger proportions of variance. Our analyses indicate that a particular focus on positive peer experiences may be useful, whereas school environments are less important. We recommend further investigating the impact of home environments and social interactions beyond parental relationships.

6.6 Chapter Summary

In this chapter I have used an MZ differences design to show that a substantial proportion of the variance in wellbeing can be explained by specific nonshared environmental influences, emphasising the value of investigating environmental influences, especially in our current genomic era. This is the first study to apply the MZ differences design to establish plausible causal influences on wellbeing in adolescence. We explained on average 5% of the total variance in our subjective and eudaimonic wellbeing indicators, which is substantial compared to the variance currently explained by common genetic variants (Baselmans & Bartels, 2018). Further research is needed to better understand plausible causal mechanisms that influence wellbeing. The next chapter extends my exploration of environmental influences on wellbeing in adolescence by assessing the effect of characteristics of the physical environment in which we live.

Chapter 7. Living in a scenic environment positively influences wellbeing in adolescence beyond the effects of urban-rural classification and green space

7.1 Chapter Overview

Twin studies have demonstrated the importance of environmental influences on wellbeing in adolescence (Bartels, 2015; Haworth, Carter, Eley, & Plomin, 2015). My analyses have supported this (see Chapter 5 and Chapter 6) suggesting that the environment provides possible mechanisms for wellbeing in adolescence. Though most research focuses on social factors within the environment, there is evidence that aspects of the physical environment can influence wellbeing (e.g. Brereton, Clinch, & Ferreira, 2008). In this chapter, I explore the impact of one aspect of the physical environment on subjective wellbeing in adolescence.

Previous research has largely focused on the impact of urbanisation and green space (MacKerron & Mourato, 2013; White, Alcock, Wheeler, & Depledge, 2013). However, the physical characteristics of our environment extend beyond whether we live in a city or close to a park. A newly available crowd-sourced dataset, *ScenicOrNot*, provides a measure of the aesthetics of the environment. This dataset set has previously been used to explore the relationship between living in a scenic environment and subjective health (Seresinhe, Preis, & Moat, 2015) but so far no research has explored the association with subjective wellbeing or used an adolescent sample.

In this chapter I aim to:

1. Evaluate the use of a crowd-sourced measure that captures a subjective quality of the physical environment.
2. Estimate the impact of living in a scenic environment on subjective wellbeing and subjective health in adolescence, beyond the effects of urban-rural classification and proportion of green space.

7.2 Introduction

Increasing urbanisation across western society has led to more focus on the impact of the physical environment on human health and behaviour. Findings suggest the local physical environment can affect physical and mental health using adult samples (Maas, Verheij, Groenewegen, De Vries, & Spreeuwenberg, 2006; McKenzie, Murray, & Booth, 2013; Seresinhe et al., 2015; Sundquist, Frank, & Sundquist, 2004), yet we have little knowledge of the effects of the physical environment on life outcomes during adolescence. Recent twin studies highlight the importance of environmental influences on wellbeing in adolescence (Bartels, 2015; Haworth et al., 2015; Wootton, Davis, Mottershaw, Wang, & Haworth, 2017), and in Chapter 6 I demonstrated that specific environmental influences can explain substantial variance in wellbeing. The effects of the physical environment may be particularly salient during adolescence when most young people lack the freedom to select where they live.

7.2.1 The impact of urban environments and green space on subjective wellbeing and mental health

The effects of an urban environment compared to a natural environment on subjective wellbeing (with components of affect and life satisfaction) have been established in adult samples using experimental methods, experience sampling methods and large cohort studies (Hartig, Evans, Jamner, Davis, & Gärling, 2003; Houlden, Weich, & Jarvis, 2017; MacKerron & Mourato, 2013; White et al., 2013). Experimental methods have found walking or being outside in a natural compared to an urban environment increases positive affect (Hartig et al., 2003; MacKerron & Mourato, 2013). These effects are substantial with increases in happiness of up to 6% in the present moment (MacKerron & Mourato, 2013). Furthermore, living near more green space is associated with slightly higher life satisfaction in large cohort studies (where a 1 standard deviation change in percentage of green space predicts a 0.035 change in life satisfaction on a 7-point scale, White et al., 2013). A review of six studies (experimental and quasi-experimental) found that simply viewing landscapes with nature compared to urban scenes increased both affect and life satisfaction (Velarde, Fry, & Tveit, 2007). It is therefore plausible that more natural and less urban environments as well as environments with more green space may increase subjective wellbeing in adolescence.

Few studies have explored the effects of urban living and green space on subjective wellbeing in childhood and adolescence. However, studies have explored negative mental health outcomes. As described previously, mental health issues including depression and anxiety are moderately correlated with subjective wellbeing (Haworth et al., 2015) and therefore research that explores environmental effects on negative mental health outcomes are informative for investigations of subjective wellbeing. Green space has been associated with fewer behavioural problems, fewer internalising symptoms, decreased depression and fewer symptoms of ADHD across ages 12 to 18 years (Amoly et al., 2014; Bezold et al., 2017; Feng & Astell-Burt, 2017; Kuo & Faber Taylor, 2004; Markevych et al., 2014). The effects are substantial considering green space is only one aspect of the physical environment, usually measured as the proportion of green space within a specified area (Bezold et al., 2017) or the distance to the closest public area of green space (Markevych et al., 2014). For example, one inter-quartile range increase in the proportion of greenness in the area was associated with 11% lower odds of high depressive symptoms in adolescence (Bezold et al., 2017). However, the effects of proximity to and quantity of green space on adolescent mental health do not consistently replicate (Amoly et al., 2014; Astell-Burt, Mitchell, & Hartig, 2014; Gubbels et al., 2016), and more rural areas, which also have more green space, have been associated with higher adolescent suicide rates (Steck, Egger, Schimmelmann, Kupferschmid, & Cohort, 2018). We need more research to untangle the direction of the association between urban environments, green space and adolescent mental health.

7.2.2 The impact of the physical environment beyond urban-rural classification and quantity of green space

One explanation for the discrepancy in findings of positive associations between green space and wellbeing could be that the composition of green space could be more important than the quantity. For example, there is some evidence that the quality of parks and green spaces in urban environments influence subjective wellbeing (for review, see Lee & Maheswaran, 2011), though it may not be more important than park quantity (Larson, Jennings, & Cloutier, 2016). However, the quality of our physical environment incorporates more than parks and green spaces (Seresinhe, Preis, & Moat, 2017; Wheeler et al., 2015), and new research suggests that the characteristics of our environment, such as urban design, influence mental health (Hosang, 2016).

Green spaces composed of trees in urban environments have been more strongly associated with subjective health and neighbourhood satisfaction than areas composed of grass (Lee, Ellis, Kweon, & Hong, 2008; Reid, Clougherty, Shmool, & Kubzansky, 2017). This may be explained by trees creating more aesthetically pleasing environments due to more visual complexity (Flannigan, 2005; Summit & McPherson, 1998). Other characteristics of the physical environment beyond urban-rural classifications and green space that have been associated with life satisfaction include the climate, proximity to a coast and proximity to transport links (Brereton et al., 2008). However, the findings again do not always replicate. For example, proximity to coast did not significantly influence life satisfaction in a large epidemiological study (White et al., 2013). These discrepancies may be because not all coastal areas are of the same quality in terms of being aesthetically pleasing, having beaches or having tourism. Therefore, characteristics of the quality of the physical environment beyond proximity or proportion may be more important to wellbeing. This has been addressed by research that measures environment quality using researcher ratings of the environment where participants live by either attending the participant's location (Annerstedt et al., 2012; Van Dillen, de Vries, Groenewegen, & Spreeuwenberg, 2012), or by using Google Street view (Odgers, Caspi, Bates, Sampson, & Moffitt, 2012). Though these measures show promising results, researcher ratings are time consuming and impractical for large scale research.

7.2.2.1 Measuring a specific quality of the physical environment: ScenicOrNot

Here we used new publicly available data that aims to capture the aesthetic quality of the physical environment without relying on self-reports or researcher intensive data collection. The *ScenicOrNot* dataset comprises crowd sourced data of multiple ratings of photos that represent almost every one kilometre grid square of the UK (Data Science Lab, 2015). Ratings were collected using a 10-point response scale ranging from 'not scenic' to 'very scenic' and raters were members of the general population with no specific training. The developers of the *ScenicOrNot* database used photos from the Geograph project ('Geograph', 2005), where the photos were originally collected to capture the salient physical features of each grid square across the UK. By February 2015, over 200,000 of the photos were rated on scenic level by at least three raters, representing approximately 95% of the UK kilometre grid squares.

As the scenic ratings of each photo are subjective, research has tried to determine the characteristics of photos with high and low scenic scores. One study used two different analyses to demonstrate that the scenic level represents the quality of the environment beyond green space (Seresinhe et al., 2015). First, colour composition analysis of the *ScenicOrNot* photos showed more scenic photos tended to have higher proportions of blue and brown pixels, but not green pixels. Second, there is only a modest correlation ($\tau = 0.20$ using Kendall's rank correlation) between *ScenicOrNot* and the proportion of green space in England, measured as the percentage of an area composed of vegetation. Furthermore, photos with features including grass and athletic fields were rated less scenic whereas photos with trees were rated more scenic (Seresinhe et al., 2017). Together, these studies suggest *ScenicOrNot* is a valuable dataset to understand the impact of the quality of the physical environment on physical and mental health beyond the quantity of green space.

At present, only one study has used the *ScenicOrNot* dataset to explore the impact of living in a scenic environment on subjective health by combining the *ScenicOrNot* dataset with census data (Seresinhe et al., 2015). This study found that living in more scenic environments predicted better subjective health across urban, suburban and rural areas in England, even after controlling for age, gender and six of the UK government indices of deprivation including income, employment, education, housing, living environment and crime (Seresinhe et al., 2015). Although effect sizes in this study were small, we would not expect one aspect of the physical environment to explain a large proportion of variance. However, when combined with other aspects of the physical environment, it could be part of an important influence on subjective wellbeing and subjective health.

After reviewing the literature presented here on the effect of physical environment characteristics using adult samples (MacKerron & Mourato, 2013; White et al., 2013), it seems plausible that more natural and less urban environments positively impact adolescent wellbeing, along with environments with larger proportions of green space. However, the inconsistent findings of the associations between green space, urban living and adolescent mental illness (Bezold et al., 2017; Steck et al., 2018) indicate that other environmental characteristics may be important.

7.2.3 Research aims

Our primary aim was to quantify the impact of living in a scenic environment on subjective wellbeing in a large adolescent cohort. Though life satisfaction is often measured as a single component (Lucas & Donnellan, 2012), research has suggested life satisfaction is multidimensional (Huebner, 1994). Assessing the impact of the physical environment on measures of environment satisfaction may uncover additional nuances not observed in global measures. Consequently, we assessed subjective wellbeing in adolescence using subjective happiness, life satisfaction and satisfaction with the environment. We also explored the relationship between living in a scenic environment and subjective health to compare our findings with that of Seresinhe et al. (2015).

Our secondary aim concerns the size of the area that is important for adolescent wellbeing. Little is known about how the size of the area that is used to represent the physical environment may impact individuals' mental and physical health. We are keen to assess the impact of the physical environment that an individual regularly interacts with. To explore this, we investigated the association between scenic level and subjective wellbeing and subjective health across 1 to 20 km areas from an individual's geocoded location.

7.3 Methods

7.3.1 Participants and measures

Data were collected as part of the Twins Early Development Study, as described in Chapter 3, section 3.1. Here, we used measures of subjective health, subjective happiness and life satisfaction. Subjective health was measured on the web study. Life satisfaction and subjective happiness were measured on both the book and the web data collection. The

Multidimensional Student Life Satisfaction Scale (MSLSS; Huebner, 1994), used in the web study, has an environment subscale with four items specifically related to the physical environment: ‘there are lots of fun things to do where I live’, ‘I wish I lived in a different house’, ‘I wish there were different people in my neighbourhood’ and ‘I like where I live’. The environment subscale of the MSLSS is included in the overall composite of life satisfaction and the negatively worded items are reverse scored to create the composite. Consequently, we had seven outcomes: subjective happiness, life satisfaction, subjective health, and the four environment-specific items of the MSLSS.

As characteristics of the physical environment are common to both twins, we wanted to use outcome measures aggregated on a family wide level including all families with data from either one or both twins to maximise sample size. The vast majority of our data is from families where data is available for both twins, nevertheless I performed a sensitivity analysis to test whether there were meaningful differences for mean scores calculated across both twins from one twin pair (i.e. a ‘family score’) compared with mean scores calculated for one twin. As our dataset is large, we expect *t*-tests to show significant differences. Consequently, we chose to accept a difference as meaningful if it was larger than Cohen’s d of 0.20 (indicating a small effect). The sensitivity analysis did not show any meaningful differences based on these criteria, though it is worth noting that scores on the outcome measures were slightly lower in families with only one twin’s data (Table 7.1). To maximise power, we calculated the overall mean for each of the outcome measures at a family wide level: where we had data from both twins, we calculated a mean family score. Where participants had responses for both online and postal measures of life satisfaction and subjective happiness, the mean score was taken (see Chapter 3, section 3.1.4 for sensitivity analysis).

Table 7.1 Sensitivity analysis of the difference in mean scores for families with data from both twins compared to families with data from one twin for all outcome measures

Outcome	**Mean (SD) N**		***t-test***	**Cohen's *d***
	Both twins	**One twin**		
Subjective happiness	5.15 (0.78) 5293	5.15 (1.22) 325	t(340.35) = 0.06 *p* = 0.9556	-0.003
Life satisfaction	0.00 (0.81) 5294	-0.18 (1.11) 323	t(343.59) = 2.91 *p* = 0.0038	-0.167
'there are lots of fun things to do where I live'	3.48 (1.21) 2389	3.22 (1.43) 536	t(717.01) = 3.9 *p* = 0.001	-0.186
'I wish I lived in a different house'	2.42 (1.28) 2346	2.66 (1.68) 574	t(744.18) = -3.1 *p* = 0.0017	0.146
'I wish there were different people in my neighbourhood'	3.53 (1.25) 2361	3.63 (1.60) 560	t(729.81) = -1.39 *p* = 0.1641	0.065
'I like where I live'	4.81 (0.99) 2370	4.68 (1.26) 551	t(714.94) = 2.17 *p* = 0.0303	-0.103
Subjective health	3.01 (0.64) 2402	2.92 (0.85) 525	t(659.25) = 2.25 *p* = 0.0246	-0.109

Note. N refers to number of families with data for each outcome measure, regardless of whether they have data for the physical environment characteristics.

7.3.1.1 Measuring the environment

We used three measures of the physical environment: the scenic level of the environment, the urban-rural classification, and the proportion of green space. Our main predictor was the scenic level of the environment and we controlled for the urban-rural classification and the proportion of green space as possible confounders. The process of matching these datasets with the TEDS dataset is described in the section below on data preparation.

7.3.1.1.1 ScenicOrNot

We used the publicly available *ScenicOrNot* dataset to measure the scenic level of the environment where participants lived (Data Science Lab, 2015), downloaded from http://scenic.mysociety.org/votes.tsv (now: http://scenicornot.datasciencelab.co.uk/) in May 2015 (file version created 01.02.2015). This dataset consists of crowd-sourced ratings of 212,208 photos that represent over 95% of each square kilometre of the UK. Photos were collected to represent each grid square of the UK in the Geograph project ('Geograph', 2005) and were intended to represent the human and physical features of the grid square (see Table 7.2 for examples). The dataset consists of six variables: latitude and longitude coordinates, an average scenic rating, the population variance for the scenic ratings of each photo, the individual scenic ratings per photo and a URL to the original photo. Each photo included in this dataset was rated at least three times on a 10-point scale ranging from 'not scenic' to 'very scenic' to account for subjective differences in ratings. On average, the mean rating of each photo was 4.42 and the variance in the ratings of each photo was 2.76, suggesting moderate inter-rater reliability.

Table 7.2 Examples of scenic photos across a range of scenic scores

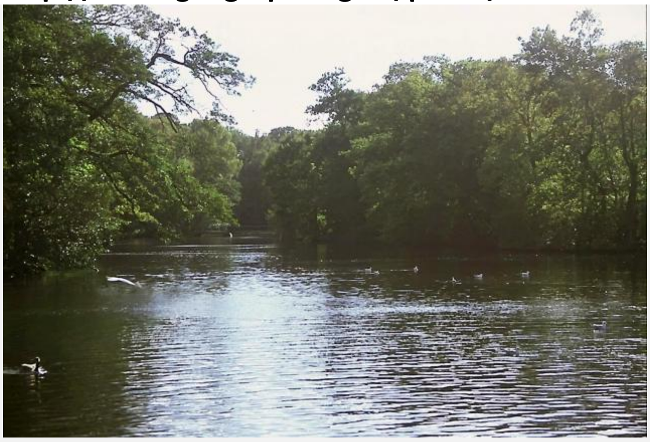
Photo	Location (latitude, longitude)	Mean scenic score (range)	Number of ratings
 **http://www.geograph.org.uk/photo/996285**	Exminster, Devon (50.6794, -3.5159200)	1.00 (1, 1)	5
 **http://www.geograph.org.uk/photo/260235**	Bicker, Lincolnshire (52.9143, -0.1763590)	2.50 (1, 4)	10
 **http://www.geograph.org.uk/photo/1888**	Raby Mere, near Bromborough (53.3260, -2.998550)	4.00 (2 – 8)	8

Photo	Location (latitude, longitude)	Mean scenic score (range)	Number of ratings
 http://www.geograph.org.uk/photo/7686	Middleton-on-The-Wolds, East Riding of Yorkshire (53.9238, -0.560784)	7 (5 – 9)	8
 http://www.geograph.org.uk/photo/835292	Newcombe Hope, Flamborough (54.1296, -0.0979765)	9.00 (7 – 10)	6

7.3.1.1.2 Urban-rural classification

To classify the extent that an area was urban, I used the 2011 Rural Urban Classification for small area geographies (RUC2011) developed by the Department of Town and Regional Planning at the University of Sheffield on behalf of the Office for National Statistics (ONS). I downloaded the data in August 2016 from the ONS Open Geography portal (http://geoportal.statistics.gov.uk). It is designed to provide a consistent rural and urban view of UK datasets across different geographic levels. The most detailed geographical level are Output Areas, which group small areas of postcodes considered socially homogenous based on characteristics of census data including household or dwelling type. Output Areas consist of a minimum of 100 residents, but averaged 309 residents in the 2011 census. There were 181,408 Output Areas across England and Wales in 2011 (171,372 in England and 10,036 in Wales). The 2011 Rural Urban Classification for small area geographies (RUC2011) assigns the Output Areas across England and Wales as urban if they were located in a 'built up' area with a population of at least 10,000, and otherwise assigns the area as rural. Output Areas categorised as urban are then subdivided into four settlement/context types and rural areas are subdivided into six settlement/context types, creating 10 classifications in total. Settlement type is assigned to each 2011 output area by dwelling density, and the context of each settlement is determined by dwelling density in the surrounding areas. The classifications are: urban major conurbation; urban minor conurbation; urban city and town; urban city and town in a sparse setting; rural town and fringe; rural town and fringe in a sparse setting; rural village; rural village in a sparse setting; rural hamlets and isolated dwellings; rural hamlets and isolated dwellings in a sparse setting. For our analyses, we ranked each type of classification, ranging from 1 for major conurbation to 10 for hamlets and isolated dwellings in a sparse setting. This meant that a higher urban-rural score indicated a more rural Output Area.

7.3.1.1.3 Green space

To measure the proportion of green space in an area, I used the generalised land use database (GLUD), developed by the ONS in 2005. This dataset is freely available from the UK government open data website (https://data.gov.uk/), where I downloaded the data in November 2016. The generalised land use database allocates all identifiable land features on the Ordnance Survey MasterMap into nine land categories for the Output Areas in England. The nine categories are domestic buildings, non-domestic buildings, roads, paths, rail, domestic gardens, green space, water, other land uses (largely hardstanding), and unclassified. Green space is defined as all vegetated areas greater than $5m^2$ except domestic gardens, regardless of accessibility. Consequently, this green space measure is considered to indicate an area's overall green ambience or greenness (CRESH, 2010). As this dataset was created in 2005, it uses the 2001 Census Output Areas as the smallest geographic level and assigns the percentage of green space to each 2001 Output Area. I calculated the percentage for each 2001 Output Area using the 'area of green space' and the 'total area of all land types' variables in the 2001 GLUD dataset.

For consistency with the urban-rural classification, which better reflects the year of wellbeing data collection, I matched the 2001 Output Areas with the 2011 Output Areas using the ONS best-fit lookup file for England and Wales (named 'Output Area 2001 to Output Area 2011 E+W Lookup'), downloaded in November 2016 from the Government open data website. This file indicates whether each 2001 Output Area has not changed, been split, been merged or anything else. In total, 6% of the Output Areas had changed due to changes in population size. To account for this, I merged the lookup dataset with the 2001 GLUD dataset based on the 2001 Output Area codes. This assigned any new 2011

Output Areas green space scores if the 2001 Output Area had not changed, had been split or anything else. However, 620 (0.36%) of the 2011 Output Areas had more than one corresponding 2001 Output Area due to merging of 2001 Output Areas or for reasons not specified, and consequently had multiple green space scores. For each 2011 Output Area that had more than one corresponding 2001 Output Area, I calculated the total percentage of green space by summing the 'area of green space' and 'total area of all land types' variables per corresponding 2001 Output Area. As a result, I assigned green space scores to all (171,372) 2011 Output Areas in England. As the green space score is a percentage, a higher score indicates more green space.

7.3.2 Data preparation

7.3.2.1 Assigning physical environment characteristics to each TEDS family

I assigned scores for the physical environment variables (scenic, urban-rural and green space scores) to the 6,284 families living in England. To do this, I first assigned a scenic, urban-rural and green space score to each km grid square of England. I then calculated the Haversine distance (in metres) between the family's location and each km grid square. The Haversine formula (Sinnott, 1984) calculates the great-circle distance between two points using latitude and longitude coordinates, accounting for the point being on a sphere. I applied the Haversine formula using the Geosphere package (Hijmans, 2016) in R.

I assigned scenic scores to each OS grid square in England (n = 156,300) by matching the latitude and longitude coordinates of each scenic photo (n = 212,208) to the OS grid square in which they are positioned. To do this, I used the spTransform() function in the rgdal package in R (Bivand et al., 2018) and the OS grid square shapefile (OSGB_Grid_1km, attained from github.com/charlesroper/OSGB_Grids). Where there was more than one scenic photo within a grid square (2.10% of observations), I calculated a mean scenic score. As the urban-rural classification and the proportion of green space are calculated for each Output Area in England (171,372 Output Areas), I needed to match the location of each km grid square to an Output Area. To do this, I used the ONS postcode directory (named ONSPD_MAY_2016_UK.csv), which matches every postcode in the UK to area geographies, including Output Areas. I matched the OS grid square to the nearest postcode in England (n = 2,144,987) by calculating the Haversine distance (in metres) between the centroid latitude and longitude coordinates of each grid square and the postcodes within 2.2 kilometres directly north or south of the grid square.

Next, for each TEDS family, I calculated the distance (in metres) between their location and the centroid of each OS grid square within 50 km directly north or south. I then created a subset of the grid squares that were less than 1,000 metres from the family's location. For this subset, I recorded the total number of grid squares and then calculated the mean, minimum and maximum distance of the grid squares from the family's location. I also calculated the mean, minimum and maximum scenic score, urban-rural classification score and green space for these photos. I then repeated this analysis a further 19 times, each time increasing the distance from the family's location by 1,000 metres. This resulted in scenic, green space and urban-rural scores for each TEDS family for circular areas around their location, expanding by 1-kilometre radius from 1 to 20 km. I then repeated this analysis to calculate urban-rural and green space scores for each family across 1 to 20 km. This resulted in a scenic, urban-rural and green space score for each TEDS family in England, for circular areas around their location ranging from 1 km radius up to 20 km. An example of my R code is provided in Appendix 7.1. As shown in Table 7.3, the mean family scenic score increased from 3.10 to 3.66 as the size of the area around the family's home increased from 1 to 20 km. The mean urban-rural scores increase as the radii increase, suggesting the surrounding area becomes more rural as the distance is increased. Finally, the percentage of green space also increases as the distance is increased.

Table 7.3 Mean scores for the environment measures: scenic level, rural-urban classification and percentage of green space

Radius (Km)	Mean Scenic score (range)	Mean Urban-Rural classification score (range)	Mean percentage of green space (range)
1	3.10 (1.00, 7.40)	3.61 (1, 10)	50.15 (0.00, 99.24)
2	3.24 (1.66, 6.19)	3.99 (1, 10)	57.12 (4.05, 99.07)
3	3.32 (1.84, 5.90)	4.32 (1, 10)	61.25 (7.62, 98.92)
4	3.38 (2.09, 5.99)	4.58 (1, 10)	64.03 (11.07, 98.88)
5	3.42 (2.19, 6.10)	4.78 (1, 10)	66.08 (14.06, 98.9)
6	3.45 (2.25, 6.00)	4.93 (1, 9.99)	67.61 (14.87, 98.88)
7	3.48 (2.31, 5.88)	5.06 (1, 9.99)	68.85 (15.50, 98.86)
8	3.50 (2.36, 5.77)	5.17 (1, 9.97)	69.88 (16.31, 98.83)
9	3.52 (2.41, 5.71)	5.27 (1, 9.97)	70.73 (17.35, 98.79)
10	3.54 (2.41, 5.67)	5.35 (1, 9.96)	71.47 (18.30, 98.76)
11	3.56 (2.43, 5.65)	5.42 (1, 9.96)	72.13 (18.42, 98.7)
12	3.57 (2.46, 5.61)	5.48 (1, 9.95)	72.70 (19.33, 98.63)
13	3.59 (2.51, 5.59)	5.53 (1, 9.95)	73.22 (20.55, 98.53)
14	3.60 (2.52, 5.59)	5.58 (1, 9.94)	73.67 (21.22, 98.38)
15	3.61 (2.54, 5.56)	5.63 (1, 9.93)	74.07 (21.82, 98.26)
16	3.62 (2.55, 5.52)	5.67 (1.01, 9.93)	74.45 (22.70, 98.24)
17	3.63 (2.56, 5.51)	5.70 (1.02, 9.91)	74.79 (23.83, 98.13)
18	3.64 (2.58, 5.48)	5.74 (1.04, 9.89)	75.12 (25.06, 98.08)
19	3.65 (2.62, 5.48)	5.77 (1.06, 9.88)	75.42 (26.59, 98.03)
20	3.66 (2.65, 5.48)	5.81 (1.10, 9.87)	75.71 (28.30, 97.98)

Note. Radius refers to the length of radii from the family's location. Descriptive statistics shown for families in England only, with available location data (N = 6,284 families).

7.3.2.2 Defining the sample

First, I excluded families that did not live in England or did not have location data. This is because I needed the location data to assign the physical environment variables (scenic level, urban-rural classification and green space), and our measure of green space was only available for England. This resulted in a total sample of 6,284 families with data for the physical environment characteristics.

Next, as the length of time living in a location may influence wellbeing, we tested whether there was a significant difference in life satisfaction, subjective happiness and subjective health between families that had never changed address (N = 4,344) and families that had changed address within the last ten years (N = 1,940). Where *t*-tests indicated a significant difference between the mean score on the wellbeing outcome, we accepted a meaningful difference as anything above a small effect (Cohen's $d > |0.20|$) in an attempt to maximise sample size.

There was a significant difference between those who had changed address within the past 10 years and those who had not for the life satisfaction items: 'there are lots of fun things to do where I live', 'I wish I lived in a different house', and 'I like where I live'. All differences indicated worse outcomes for individuals that had changed their address. However, the effect sizes were small (see Table 7.4) so to maximise power I included all participants in the analysis regardless of whether they had changed address within the last ten years.

Table 7.4 Analysis of effect of change of address within last 10 years for outcome measures

Outcome	Mean (SD) N No change of address	Mean (SD) N Change of address	*t-test*	Cohen's *d*
Subjective happiness	5.15 (0.81) 3364	5.14 (0.82) 1500	t(2851.61) = 0.374 *p* = 0.709	0.01
Life satisfaction	0.01 (0.83) 3363	-0.04 (0.84) 1499	t(2820.4) = 1.743 *p* = 0.081	0.05
'there are lots of fun things to do where I live'	3.50 (1.23) 1761	3.34 (1.26) 767	t(1430.86) = 3.009 *p* = 0.003	0.13
'I wish I lived in a different house'	4.58 (1.36) 1757	4.40 (1.44) 766	t(1383.53) = 2.981 *p* = 0.003	0.13
'I wish there were different people in my neighbourhood'	3.50 (1.31) 1758	3.41 (1.36) 767	t(1403.99) = 1.531 *p* = 0.126	0.07
'I like where I live'	4.84 (1.01) 1759	4.70 (1.10) 765	t(1353.54) = 2.899 *p* = 0.004	0.13
Subjective health	2.99 (0.67) 1761	2.97 (0.71) 768	t(1373.1) = 0.634 *p* = 0.526	0.03

Note. N refers to number of families with data for each outcome measure that live in England and have data for the physical environment characteristics.

7.3.3 Data analyses

My primary aim was to quantify the impact of living in a scenic environment on subjective wellbeing in a large adolescent cohort, after controlling for urban-rural classification and proportion of green space. I used scenic, urban-rural and green space scores within a 5 km radius from the families' locations for this analysis because the average distance travelled to school at the time of data collection was approximately 5 km (Deparment of Transport, 2012). Before starting my main analyses, I calculated the correlations between the scenic level, urban-rural classification and green space to assess the construct validity of the scenic measure. I expected that areas with a higher scenic level would also be more rural and have larger proportions of green space.

To address my primary aim, I first conducted linear regression analyses to assess the impact of a scenic environment on the outcome measures. I then conducted hierarchical regression analyses for each of the outcome measures. This framework allows for the comparison of regression models by adding predictors to a previous regression model to understand if additional predictors improve model fit (Field, 2009). My first linear model calculated the impact of the urban-rural classification and green space on the outcome. I then added the scenic level as a predictor in a second model. To assess whether additional predictors significantly improved model fit, I calculated the difference in the percentage of variance explained by the new model (urban-rural classification, green space and scenic level) and the previous model (urban-rural classification and green space). As adding a predictor to a regression model always explains more variance, I assessed whether this improvement was significant using F-statistics calculated from ANOVA model comparisons.

As a secondary research aim, I was keen to understand the impact of the physical environment that an individual regularly interacts with. Little is known about the size of this physical environment. I therefore repeated the above analyses for circular areas around the families' locations for 1 to 20 kilometre radii.

7.4 Results

First, I calculated the correlation between urban-rural, green space and the scenic scores for every TEDS family with complete environment data (n = 6284) using a 5 km circular area. I found high correlations between scenic level and urban-rural classification (0.782; 95% CIs = 0.772, 0.792), and scenic level and green space (0.776; 0.766, 0.786). Both correlations were in the expected direction and indicate that higher scenic scores are associated with more rural areas (high urban-rural classification scores) and areas with larger proportions of green space. As expected, more rural areas are also strongly correlated with larger proportions of green space (0.919; 0.915, 0.923). The urban-rural classification and the proportion of green space are more similar to each other than they are to the scenic level, though there is substantial similarity between these physical environment characteristics.

The single linear regression analyses indicated that the scenic level significantly explained variance in the life satisfaction items, ‘there are lots of fun things to do where I live’ and ‘I wish there were different people in my neighbourhood’, where more scenic environments were negatively associated with both items. Unexpectedly, more scenic environments predicted less satisfaction with fun things to do. There was no significant effect of living in a scenic environment on any of the other outcomes.

A multiple regression model including urban-rural classification, green space and scenic level significantly explained variance in life satisfaction and the items ‘there are lots of fun things to do where I live’, ‘I wish I lived in a different house’ and ‘I like where I live’ (see Table 7.5). The hierarchical regression showed that including the scenic level in a model with urban-rural classification and green space significantly improved model fit compared with a model of urban-rural classification and green space. In contrast to the single linear regression, living in a more scenic environment had a positive (as opposed to negative) impact on satisfaction with ‘fun things to do where I live’ over and above the effects of the urban-rural classification and green space. However, the scenic level had a negative effect on ‘I wish I lived in a different house’, where a more scenic environment was associated with a higher desire to live in a different house. Across all outcomes the effect of the scenic level was small, ranging from explaining 0.10% (life satisfaction) to 0.56% (‘I like where I live’) of the variance in the outcomes. The total variance explained by a model including urban-rural , green space and scenic scores was also small for all outcomes, reaching a maximum of 2.34% for the item ‘there are lots of fun things to do where I live’. No regression model significantly predicted subjective happiness or subjective health, suggesting physical environment characteristics are not important for these measures in adolescence.

Interestingly, when assessed in the full model, the urban-rural classification had a negative effect on life satisfaction and no effect on any other outcome. The percentage of green space had a negative effect on ‘there are lots of fun things to do where I live’ and no effect on any other outcome. These findings suggest that living in more rural areas and areas with larger proportions of green space may have a small negative impact on life satisfaction in adolescence.

Table 7.5 Summary of hierarchical regression analyses to understand the effect of a scenic environment on positive outcomes during adolescence, after controlling for urban-rural classification and green space.

5 km	**Subjective Happiness** (n = 4864)				**Life Satisfaction** (n = 4862)				**Subjective Health** (n = 2529)			
	β (95% CIs)	t-value (*p*)	R^2	F statistic	β (95% CIs)	t-value (*p*)	R^2	F statistic	β (95% CIs)	t-value (*p*)	R^2	F statistic
Model 1: Scenic only												
Scenic	0.03 (-0.02, 0.07)	1.17 (0.24)			0.04 (0.00, 0.08)	1.81 (0.07)			0.03 (-0.02, 0.08)	1.18 (0.24)		
Model 1 statistics			0.03	F(1, 4862) = 1.36 *p* = 0.24			0.07	F(1, 4860) = 3.27 *p* = 0.07			0.05	F(1, 2527) = 1.38 *p* = 0.24
Model 2: Urban-rural classification + green space												
Urban-rural classification	-0.01 (-0.04, 0.01)	-1.07 (0.28)			-0.02 (-0.05, 0.00)	-1.71 (0.09)			-0.02 (-0.05, 0.01)	-1.17 (0.24)		
Green space	0.00 (0.00, 0.01)	1.61 (0.11)			0.00 (0, 0.01)	1.95 (0.05)			0.00 (0.00, 0.01)	1.31 (0.19)		
Model 2 statistics			0.07	F(2, 4861) = 1.82 *p* = 0.16			0.08	F(2, 4859) = 1.93 *p* = 0.15			0.07	F(2, 2526) = 0.87 *p* = 0.42
Model 3: Urban-rural classification + green space + scenic level												
Urban-rural classification	-0.01 (-0.04, 0.01)	-1.09 (0.28)			-0.03 (-0.06, 0.00)	-2.25 (0.02)			-0.02 (-0.05, 0.01)	-1.51 (0.13)		
Green space	0.00 (0.00, 0.01)	1.51 (0.13)			0.00 (0.00, 0.00)	1.36 (0.17)			0.00 (0.00, 0.00)	0.88 (0.38)		
Scenic level	0.01 (-0.06, 0.08)	0.21 (0.83)			0.08 (0.01, 0.15)	2.22 (0.03)			0.06 (-0.02, 0.14)	1.47 (0.14)		
Model 3 statistics			0.08	F(3, 4860) = 1.23 *p* = 0.30			0.18	F(3, 4858) = 2.93 *p* = 0.03			0.15	F(3, 2525) = 1.3 *p* = 0.27
Difference in Model 2 and Model 3			ΔR^2 = 0.00	F(1, 4860) = 0.05 *p* = 0.83			ΔR^2 = 0.10	F(1, 4858) = 4.95 *p* = 0.03			ΔR^2 = 0.09	F(1, 2525) = 2.17 *p* = 0.14

Table 7.5 (continued) Summary of hierarchical regression analyses to understand the effect of a scenic environment on positive outcomes during adolescence, after controlling for urban-rural classification and green space.

5 km	**'there are lots of fun things to do where I live'** (n = 2528)				**'I wish I lived in a different house'** (n = 2523)			
	β (95% CIs)	t-value (*p*)	R^2	F statistic	β (95% CIs)	t-value (*p*)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.16 (-0.25, -0.07)	-3.51 (0.0005)			0.10 (0.00, 0.20)	1.93 (0.05)		
Model 1 statistics			0.48	F(1, 2526) = 12.31 *p* = 0.0005			0.15	F(1, 2521) = 3.73 *p* = 0.05
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.01 (-0.04, 0.06)	0.38 (0.71)			-0.02 (-0.08, 0.04)	-0.57 (0.57)		
Green space	-0.01 (-0.02, 0.00)	-3.15 (0.002)			0.00 (0.00, 0.01)	0.67 (0.50)		
Model 2 statistics			1.94	F(2, 2525) = 25.01 *p* = $1.76 \text{x} 10^{11}$			0.02	F(2, 2520) = 0.24 *p* = 0.79
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	-0.01 (-0.07, 0.04)	-0.46 (0.64)			-0.04 (-0.10, 0.02)	-1.29 (0.20)		
Green space	-0.01 (-0.02, -0.01)	-3.90 (0.0001)			0.00 (-0.01, 0.01)	-0.10 (0.92)		
Scenic level	0.24 (0.10, 0.39)	3.22 (0.001)			0.25 (0.08, 0.41)	2.87 (0.004)		
Model 3 statistics			2.34	F(3, 2524) = 20.18 *p* = $6.35 \text{ x} 10^{13}$			0.34	F(3, 2519) = 2.89 *p* = 0.03
Difference in Model 2 and Model 3			$\Delta R^2 = 0.40$	F(1, 2524) = 10.34 *p* = 0.001			$\Delta R^2 =$ 0.32	F(1, 2519) = 8.21 *p* = 0.004

Table 7.5 (continued) Summary of hierarchical regression analyses to understand the effect of a scenic environment on positive outcomes during adolescence, after controlling for urban-rural classification and green space.

5 km	'I wish there were different people in my neighbourhood' (n = 2525)				'I like where I live' (n = 2524)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.11 (-0.20, -0.01)	-2.15 (0.03)			0.07 (-0.01, 0.15)	1.82 (0.07)		
Model 1 statistics			0.18	F(1, 2523) = 4.61 p = 0.03			0.13	F(1, 2522) = 3.31 p = 0.07
Model 2: Urban-rural classification + green space								
Urban-rural classification	-0.03 (-0.09, 0.03)	-1.00 (0.32)			0.00 (-0.05, 0.04)	-0.15 (0.88)		
Green space	0.00 (-0.01, 0.01)	-0.34 (0.74)			0.00 (-0.01, 0.00)	-0.08 (0.94)		
Model 2 statistics			0.43	F(2, 2522) = 5.5 p = 0.004			0.01	F(2, 2521) = 0.16 p = 0.85
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	-0.04 (-0.10, 0.02)	-1.18 (0.24)			-0.03 (-0.07, 0.02)	-1.11 (0.27)		
Green space	0.00 (-0.01, 0.00)	-0.54 (0.59)			0.00 (-0.01, 0.00)	-1.07 (0.28)		
Scenic level	0.07 (-0.09, 0.23)	0.81 (0.42)			0.24 (0.12, 0.37)	3.78 (0.0002)		
Model 3 statistics			0.46	F(3, 2521) = 3.89 p = 0.01			0.57	F(3, 2520) = 4.86 p = 0.002
Difference in Model 2 and Model 3			ΔR^2 = 0.03	F(1, 2521) = 0.65 p = 0.42			ΔR^2 = 0.56	F(1, 2520) = 14.26 p = 0.0002

Note. Beta coefficients (with 95% confidence intervals) are standardised. N = number of families, which ranges 2,546 to 4,930 as subjective happiness and life satisfaction were measured on both forms of data collection. Note that this is smaller than the 6,284 families with data for the physical environment characteristics because families were required to have data for the outcome measure as well as the physical environment. Only families with complete environment data were included. R^2 represents total percentage of variance explained for the model, *F*-statistic (with *p* value) indicates model fit. ΔR^2 indicates the difference in R^2 between the model and the previous model, with the corresponding *F*-statistic (with *p* value) indicating whether the additional predictor significantly improves the previous model. The ΔR^2 and corresponding *F*-statistic were calculated using ANOVA model comparisons of the regression models.

7.4.1 Secondary analysis: what size of the environment is important for adolescent wellbeing?

By repeating my analysis for circular areas ranging 1 km to 20 km radii around the families' locations, I was able to estimate the size of the area of the environment that has the most impact on my outcome measures. First, the single linear regressions for the scenic level indicated that a scenic level did not explain variance in subjective happiness or life satisfaction, but did significantly explain variance across some areas in subjective health and the environment satisfaction items. However, the effects were small (Figure 7.1). The largest effect was on the item 'there are lots of fun things to do where I live', explaining up to 0.80% of the variance at 16 km.

Second, at all distances, the full models (urban-rural classification, green space and scenic level) for subjective happiness and subjective health fit poorly. This indicates that urban-rural, green space and scenic scores do not explain any variation in subjective happiness or subjective health. For all other measures, adding the scenic level to a model of urban-rural classification and green space significantly improved the fit across at least one distance (Figure 7.2), though the proportion of variance explained by all models was small. Interestingly, little variance in 'there are fun things to do where I live' is explained by the scenic level in the full model compared to the single regression, suggesting that the scenic level has little effect on 'there are fun things to do where I live' after accounting for urbanicity and green space.

As shown in Figure 7.2, it appears that the predictors have most impact on the outcomes at areas of approximately 2 to 3 km radii. The scenic level of the environment explains significant proportions of variance at smaller areas for all life satisfaction items. This suggests that areas smaller in size around individual's homes may be more important to wellbeing than larger areas.

The mean proportion of variance explained by the full models that significantly fit the data across the outcome measures and across all areas was 0.38%, and the mean additional variance explained by adding the scenic level to a model of urban-rural classification and green space was 0.10%. The largest proportion of variance explained in the outcomes was in the item, 'there are lots of fun things to do where I live', which was significant across all areas and explained a maximum of 2.96% at 3 km. However, the scenic level only explained an additional 0.21% to 0.55% of the variance across 2 to 6 km areas, suggesting urban-rural classification and green space were more important to the item 'there are lots of fun things to do where I live' (see Appendix 7.2 for full statistics).

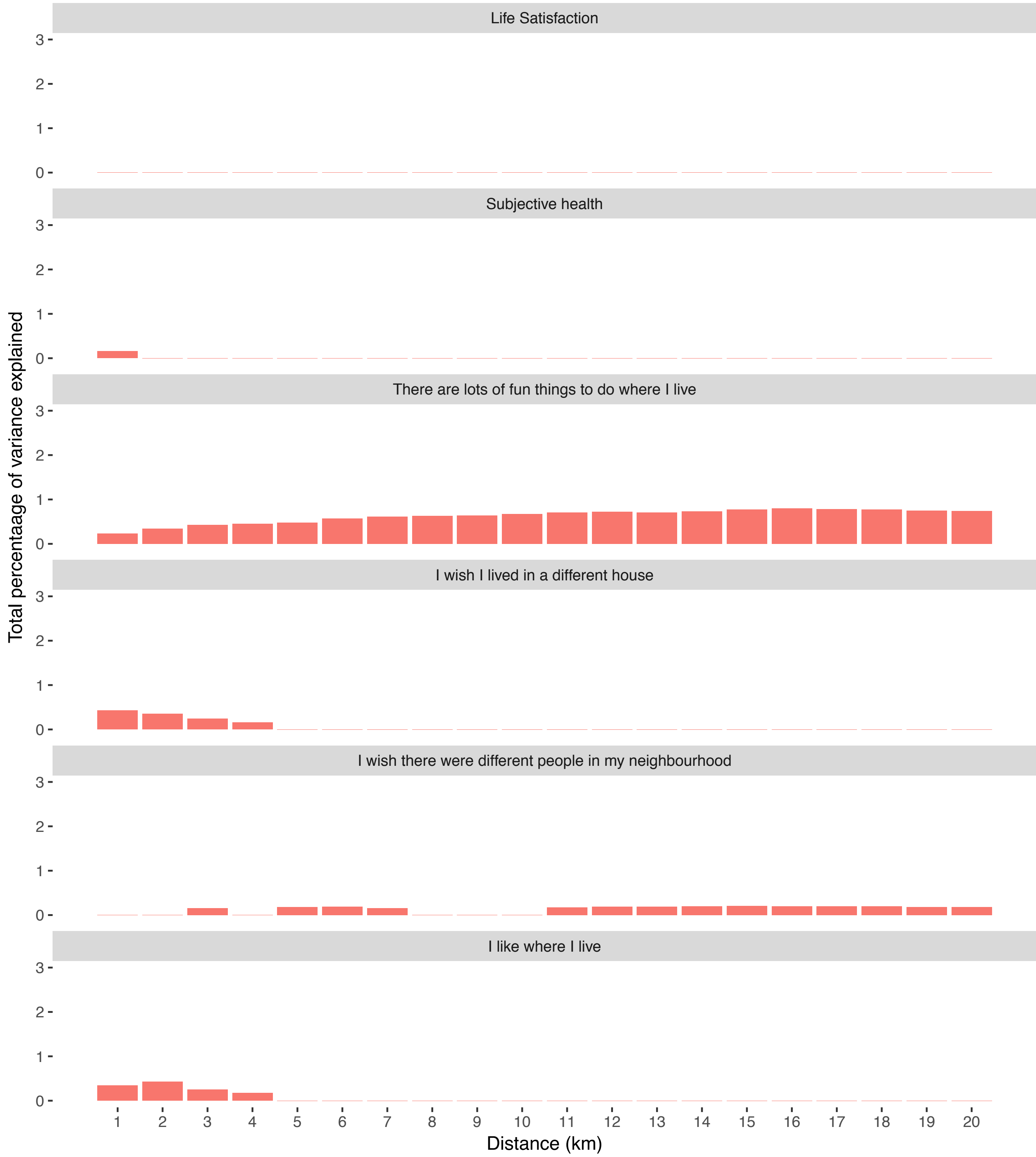


Figure 7.1 The percentage of variance explained by the scenic level for each positive outcome.
Note. Bars are only shown for models that significantly fit the data. Subjective happiness is not shown as no model fit significantly. Full statistics are reported in Appendix 7.2.

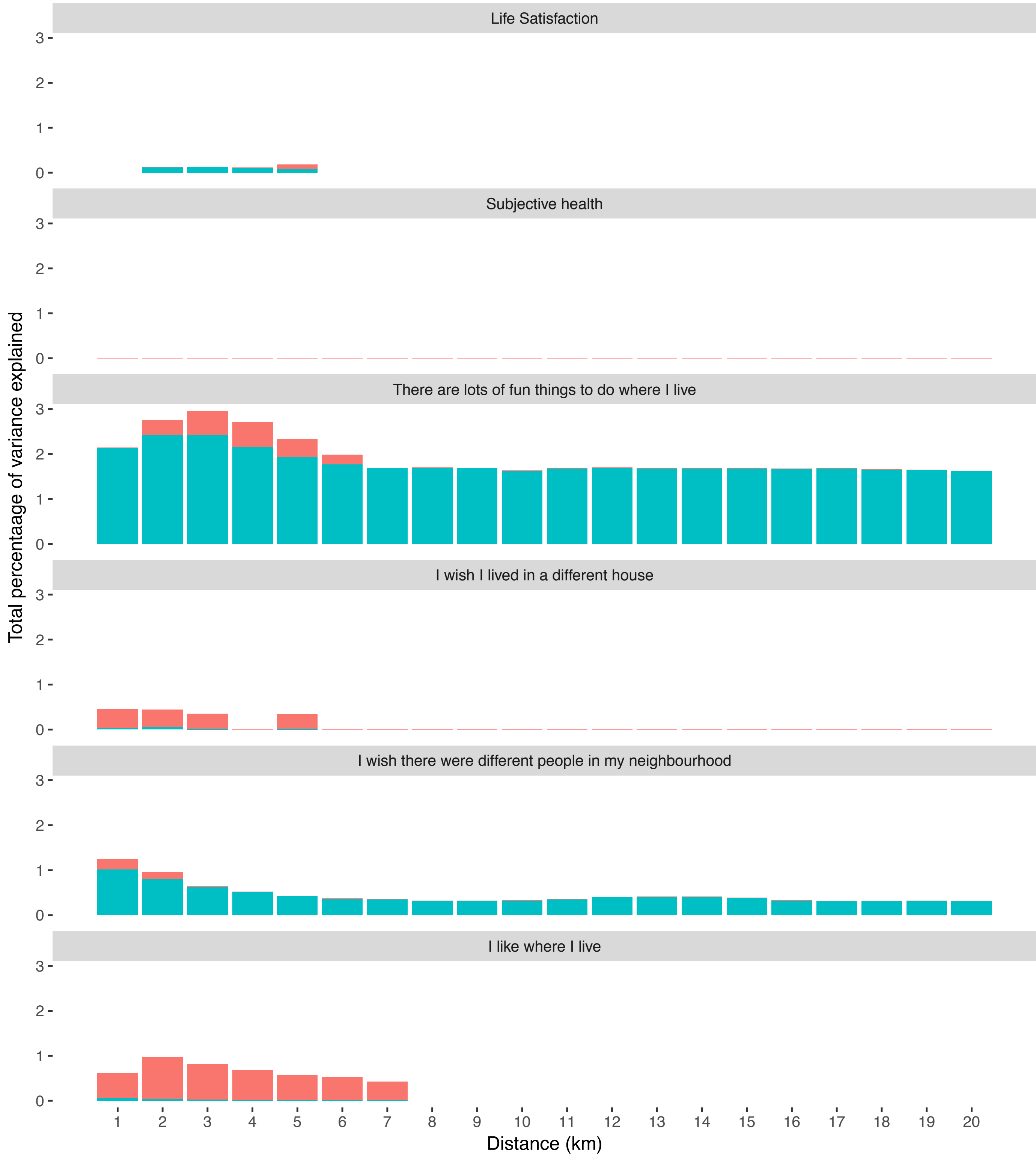


Figure 7.2 The percentage of variance explained by a model of urban-rural classification, green space and scenic level for each positive outcome. Green bars indicate the percentage of variance explained by a model with urban-rural and green space scores only. Red indicates the additional variance explained by the full model beyond the variance explained by a model with urban-rural and green space scores.
Note. Bars are only shown for models that significantly fit the data. Subjective happiness is not shown as no model fit significantly. Full statistics are reported in Appendix 7.2.

7.5 Discussion

This chapter explored the impact of a scenic environment on subjective wellbeing and subjective health during adolescence. We found that, within a circular area of 5 km, living in a more scenic environment had a small but positive effect in addition to the effect of the urban-rural classification and the proportion of green space on overall life satisfaction and satisfaction with specific aspects of the environment including perception of fun things to do, satisfaction with your house and liking where you live. Furthermore, we demonstrated the potential benefit of using measures that capture specific characteristics of environment quality for mental health research.

7.5.1 The effect of living in a scenic environment on subjective wellbeing and subjective health

The effect sizes we report are small but perhaps expected given the scenic level is one characteristic of the physical environment and many factors influence subjective wellbeing in adolescence (Asbury, Moran, & Plomin, 2016; Balluerka, Gorostiaga, Alonso-Arbiol, & Aritzeta, 2016). We found that the physical environment explained more variance in subjective wellbeing than specific genetic influences (genome-wide significant hits currently explain only approximately 0.01%, Okbay et al., 2016) and less than peer and parental relationships (approximately 6% total variance across web and booklet measures, see Chapter 6). Our findings extend research exploring the effect of a scenic environment to subjective wellbeing and health in adolescence. First, no model significantly explained variance in subjective health across any sized area, suggesting the scenic level, urban-rural classification and green space have little impact on subjective health in adolescence, unlike findings using adults (Seresinhe et al., 2015). This could be due to adults having more choice over where they live and selecting areas that suit their lifestyle, though we do not have enough understanding of how characteristics of the physical environment influence subjective health to draw strong conclusions.

Second, we found that our models had a small impact on life satisfaction (only 0.18%) but no impact on subjective happiness, which suggest it would be useful for research to use multiple indicators to capture the specific effect of the physical environment on subjective wellbeing, which is not current practice (Hartig et al., 2003; Krekel, Kolbe, & Wüstemann, 2015; MacKerron & Mourato, 2013; White et al., 2013). We also found the scenic level had most impact on satisfaction with liking where you live, which was larger than the effect of urban-rural classification and green space. In contrast, green space was more important than the scenic level for satisfaction with fun things to do but in the opposite direction, where more green space was associated with less satisfaction. It is plausible that living in a scenic environment may partially mitigate the negative effects of living in urban areas and areas with less green space observed with subjective wellbeing (Hartig et al., 2003; Houlden et al., 2017; MacKerron & Mourato, 2013; White et al., 2013). Yet it would be costly and time consuming to improve the aesthetics of areas where people live to test this theory. First, we need a greater understanding of the mechanisms by which various physical environment characteristics impact life satisfaction. Furthermore, as physical environments may be related to eudaimonic wellbeing (Houlden et al., 2017), future research should extend our work to explore the impact of the scenic environment on eudaimonic wellbeing indicators.

Third, we saw that the proportion of variance explained differed across the different sized areas we measured. This is the first attempt to understand the size of the area of the physical environment that is important, and we found that measuring physical characteristics within areas of approximately 2 to 3 km explained most variance. This suggests that a smaller surrounding area, perhaps considered walkable, is most important for subjective wellbeing and subjective health in adolescence. We need more accurate methods to measure the actual area that individuals interact with to really understand how the physical environment impacts subjective wellbeing and subjective health. This could be achieved using real-time location data collected via smartphones, assessing the quality of the physical environment using photos provided by participants (Hosang, 2016; Quercia, Schifanella, & Aiello, 2014). Combined with psychometric scales delivered within smartphone apps, these methods help us to understand the characteristics of an environment that are important for mental health (Hosang, 2016). For example, the photos that participants choose to share may be influenced by their current level of mental health and wellbeing, therefore analyses of the environmental features captured within the photos may help to explain how the physical environment shapes wellbeing and has implications for urban design.

7.5.2 The usefulness of measures that capture specific characteristics in the physical environment

We have shown that a measure designed to capture a subjective quality of the physical environment has construct validity. The scenic measure was moderately corelated with both green space and urban-rural classification in the expected direction, where more scenic areas are also greener and more rural. In line with previous research (Seresinhe et al., 2017), the correlations were less than 0.80, suggesting the scenic level captures more than an area's greenness or urban-rural classification. Furthermore, finding stronger associations with our environment satisfaction outcomes than with our more general subjective wellbeing and subjective health outcomes also indicates predictive validity. This demonstrates it is possible to capture more subjective qualities of the physical environment using measures that go beyond objective land categorisation systems and provides support for research using these types of measures (Generaal, Timmermans, Dekkers, Smit, & Penninx, 2018; Hosang, 2016; Quercia et al., 2014). If we can combine datasets that capture more subjective qualities of the physical environment with large-scale wellbeing data, we can further understand the mechanisms that facilitate the relationship between the physical environment and subjective wellbeing.

However, there are also limitations in the use of these subjective measures of the physical environment. First, it is possible that our scenic measure does not directly measure the scenic level and instead represents a confounding factor such as social deprivation, where higher scenic scores indicate less social deprivation and larger investment into local areas. However, there is some evidence that the magnitude of investments into parks and green spaces, which is higher in more affluent areas, is not associated with subjective wellbeing (Larson et al., 2016) and a previous study using the *ScenicOrNot* dataset found an effect on subjective health even when controlling for six of the UK government indices of deprivation (Seresinhe et al., 2015). Second, the scenic measure contains noise from crowd-sourced ratings of the photos where raters receive no training and it is possible that a single rater may rate the same photo more than once. This is somewhat controlled as photos are randomly shown to raters, making it unlikely the same rater will see the same photo twice and photos are only included in the *ScenicOrNot* dataset when rated at least three times. Given the likely noise in the measure of the scenic level, we may have underestimated the true effect of a scenic environment.

7.5.3 Limitations of combining large-scale datasets

My research demonstrates that using a crowd-sourced measure of the scenic level is a potentially valid way to capture one aspect of the physical environment without relying on self-reports, which could be biased, or researcher ratings of the environment, which are time consuming (Annerstedt et al., 2012; Odgers et al., 2012; Van Dillen et al., 2012). However, our approach also has limitations due to the way we assigned environmental scores to the families and the time of data collection of the environment measures. We estimated environment scores within a circular area of 5 km radius from our participants' home locations, but we do not know how participants actually interact with their local environment and it is unlikely to be in a complete circle. Furthermore, the environment datasets were collected at different times to the outcome measures and so it is possible the environment measures are not representative of the environment at the point of wellbeing data collection. For example, the scenic photos were taken across a number of years and may not represent our participants' location due to housing development. We found that approximately 6% of the Output Areas in England had been recategorized from 2001 to 2011 due to changes in population density. Though this indicates that housing development may not have had a large impact on changes in the scenic environment, it is impossible to tell without comparisons of photos from the same location across multiple years. The environment measures were also collected at different times to each other, which may have lowered the correlations we observed between the environment measures. This may mean that there is larger overlap in urban-rural, green space and scenic scores than we have assumed, and the true additional effect of the scenic level beyond the effect of urban-rural classification and green space could be smaller than we observed.

Furthermore, as with all correlational studies of this nature, it is possible that unmeasured factors are causing the observed relationship. For example, it is possible that demographic factors such as socio-economic position, psychological factors such as personality, or mental health outcomes such as anxiety and depression are moderating the observed relationship between our physical environment factors and life satisfaction. Previous research has found a small effect of living in a scenic environment on subjective health even when controlling for age, gender and six of the UK government indices of deprivation including income, employment, education, housing, living environment and crime (Seresinhe et al., 2015). It is a limitation of my study that I did not control for confounders, which may have given more power to detect the small effects we observe. However, combining even more geographical datasets may have simply added noise to the analyses. The possible influence of these factors on subjective wellbeing, and particularly in adolescence, should be explored further.

Finally, by combining many datasets with different wellbeing indicators across a range of areas, multiple testing is an issue. Using a *p* value of 0.05, we would expect by chance 21 of the 420 reported models to be false positives. We found that over half of our models were significant, suggesting that at least some of our models are unlikely to have reached significance purely by chance. We could correct for multiple testing using Bonferroni or the Benjamini-Hochberg procedure, which uses false discovery rates (Benjamini & Hochberg, 1995). However, all analyses reported here were exploratory, and over correcting for false positives also introduces a higher probability of false negatives. Consequently, I have reported the models that were statistically significant at a *p* value of 0.05 and concentrated on effect sizes (Figure 7.1 and Figure 7.2). These findings are suggestive of relationships that warrant future research, but alone do not provide enough evidence to draw strong conclusions. Consequently, it is important to emphasise that there appears to be a relationship between characteristics of the physical environment and satisfaction with where you live in adolescence, which could be investigated further.

7.6 Chapter Summary

In this chapter I have demonstrated the potential use of a measure that aims to capture a specific subjective quality of the physical environment. The high correlations between the scenic level and urban-rural classification and green space demonstrate that the scenic measure has construct validity and also captures qualities of the environment beyond urban classification and greenness. Future research would benefit from combining more measures of the subjective quality of the environment to understand which physical environment characteristics matter most for subjective health and subjective wellbeing. I also demonstrated that living in a scenic environment has a small positive impact on life satisfaction and satisfaction with specific aspects of your environment beyond the effects of urban-rural classification and green space, and has no impact on subjective happiness and subjective health in adolescence. This is the first study to show that subjective physical environment qualities are associated with adolescent wellbeing, albeit with small effects.

Chapter 8. Discussion

Wellbeing has been defined as an overarching construct that represents subjective and eudaimonic wellbeing (Biswas-Diener, Kashdan, & King, 2009; Disabato, Goodman, Kashdan, Short, & Jarden, 2016; Kashdan, Biswas-Diener, & King, 2008). In this thesis, I explored the relationship between subjective wellbeing and a diverse range of eudaimonic wellbeing indicators in adolescence. First, I aimed to understand which positive traits were best considered as components of wellbeing and which traits were correlates of wellbeing. Second, I aimed to identify the general and specific effects across subjective and eudaimonic wellbeing indicators. The main findings from each chapter are summarised in Table 8.1. In this chapter, I discuss the implications of the findings for understanding how subjective wellbeing and eudaimonic wellbeing are related with a focus on adolescence.

Table 8.1 Summary of the main findings from each empirical chapter of the thesis

Chapter	Main findings
4 – Phenotypic relationship between diverse wellbeing indicators	• 54% of the relationship between our wellbeing indicators was explained by two overarching components, which we have described as *flourishing* and *aspirational drive* • *Flourishing* included wellbeing indicators representing both subjective and eudaimonic wellbeing and *aspirational drive* included eudaimonic wellbeing indicators related to cognitive functioning • We found little empirical evidence for the theoretical distinction of subjective and eudaimonic wellbeing
5 – Bivariate relationship between diverse wellbeing indicators	• Univariate genetic and environmental estimates for *Flourishing* and *aspirational drive* indicated both genetic and environmental influences are important to wellbeing during adolescence • Genetic correlations between the our two wellbeing components was substantial (0.72) and the nonshared environmental correlations was lower (0.49) • PCA using the genetic and the environmental correlations between our 14 wellbeing measures showed a similar pattern to the phenotypic PCA • Research needs to explore similarities and differences in the specific nonshared environmental influences across diverse wellbeing indicators
6 – Specific environmental influences on wellbeing	• We did not identify specific environmental influences on *flourishing* or *aspirational drive* • We explained a substantial proportion of the total variation in subjective wellbeing: 11% in life satisfaction and 7% in subjective happiness • Peer relationships were the most important environmental factor, explaining 12% of the nonshared environmental influences on subjective wellbeing • In our current genomic era, we must not forget the complementary value of environmental research for understanding individual differences in behavioural outcomes
7 – The impact of a scenic environment on wellbeing	• The scenic dataset appears a reliable way to capture qualities of the environment beyond just urban classification and greenness, with strong correlations with the urban-rural classification (0.78) and green space (0.78) • Within a 5 km circular area, living in a scenic environment has a small but positive effect on life satisfaction, beyond the effects of urban classification and green space • There is potential to explain variance in subjective wellbeing using measures that capture specific qualities of the physical environment

8.1 How are subjective wellbeing and eudaimonic wellbeing indicators related?

There is support for wellbeing defined as an overarching construct that incorportates both subjective and eduaimonic wellbeing both theoretically and experimentally from longitudinal studies and genetically informative studies (Biswas-Diener et al., 2009; Kashdan et al., 2008). Generally, wellbeing as an overarching construct is structured in three different ways: with one component of subjective wellbeing and one component of eudaimonic wellbeing (Diener et al., 2010; Henderson & Knight, 2012; Waterman, 2008), with one component of subjective wellbeing and multiple components of eudaimonic wellbeing (Seligman, 2012; Su, Tay, & Diener, 2014), and with multiple components of subjective wellbeing and multiple components of eudaimonic wellbeing (Keyes, 2002). Yet with few studies and varied measures of wellbeing, it is difficult to decide which structure is most plausible. For example, across the 20 instruments I identified in Chapter 1 as designed to measure eduaimonic wellbeing, 38 different psychological traits were used as wellbeing indicators. I have contributed to the understanding of how subjective wellbeing and eudaimonic wellbeing indicators are related using a diverse range of positive traits. Using this diverse range of positive traits uniquely in a large twin sample, I explored the relationship between subjective wellbeing and eudaimonic wellbeing phenotypically, genetically and environmentally.

My findings support an overarching structure of wellbeing composed of multiple subjective wellbeing and multiple eudaimonic wellbeing indicators. In Chapter 4, I identified two components of wellbeing from my PCA analysis that represented wellbeing as an overarching construct. I concluded that phenotypically, wellbeing in my analyses was best defined using both subjective wellbeing indicators and eudaimonic wellbeing indicators

(Figure 8.1a). I found little empirical evidence for the theoretical distinction between subjective and eudaimonic wellbeing.

In Chapter 5, I extended our understanding of wellbeing in adolescence by exploring the genetic and environmental aetiology of my two wellbeing components, which I termed *flourishing* and *aspirational drive*. I found that genetic influences explained more variance in the *flourishing* component whereas environmental influences explained more variance in *aspirational drive* but that genetic influences were largely responsible for the moderate correlation (0.60) between the wellbeing indicators (bivariate heritability = 0.62). I also found that these subjective and eudaimonic wellbeing indicators shared moderate genetic overlap. This supports previous findings of the genetic aetiology of eudaimonic and subjective wellbeing (Caprara et al., 2009; Franz et al., 2012; Gatt, Burton, Schofield, Bryant, & Williams, 2014; Keyes, Myers, & Kendler, 2010) and extends the findings to include diverse traits. In line with previous research using Ryff's measure of psychological wellbeing to represent eudaimonic wellbeing (Franz et al., 2012; Keyes et al., 2010), I also found modest environmental overlap between the wellbeing indicators, suggesting that environments affect the components of wellbeing in largely unique ways. When I characterised the complex genetic and environmental relationship between the diverse wellbeing indicators using PCA, I found similar patterns to the phenotypic relationship. Genetically, the first component additionally included hopefulness and subjective health, but largely matched the phenotypic structure of *flourishing* (Figure 8.1b). Whereas environmentally, the relationship between the indicators was more complex and two PCA components were required to represent the *flourishing* component (Figure 8.1c). This additional environmental complexity could be due to measurement error, which is captured in the nonshared environmental influences in twin models (Plomin, DeFries, Knopik, & Neiderheiser, 2013) and is plausible given that the first component includes loadings from web measures of eudaimonic wellbeing, whereas the second component includes loadings from booklet measures of eudaimonic wellbeing. However, this does not explain why not all book and web measures load onto the components, suggesting that there are still some traits that represent wellbeing and others that are best considered correlates of wellbeing.

8.1.1 The relationship between subjective wellbeing and eudaimonic wellbeing compared to subjective wellbeing and mental health problems

From my research and from previous literature (Caprara et al., 2009; Franz et al., 2012; Gatt et al., 2014; Keyes et al., 2010), we observe moderate genetic overlap and modest nonshared environmental overlap in subjective wellbeing and eudaimonic wellbeing, giving strength to the argument that wellbeing is an overarching construct that encompasses both subjective and eudaimonic wellbeing. The size of this overlap is substantial. The average genetic correlation (rA) was approximately 0.74 and the average nonshared environmental correlation (rE) was approximately 0.41 between life satisfaction and our seven eudaimonic wellbeing indicators that loaded onto the *flourishing* component (displayed in Figure 8.1a). We found similar but slightly lower correlations between subjective happiness and our seven eudaimonic wellbeing indicators (rA = 0.68; rE = 0.35), suggesting there could be a stronger relationship between life satisfaction and eudaimonic wellbeing than between subjective happiness and eudaimonic wellbeing.

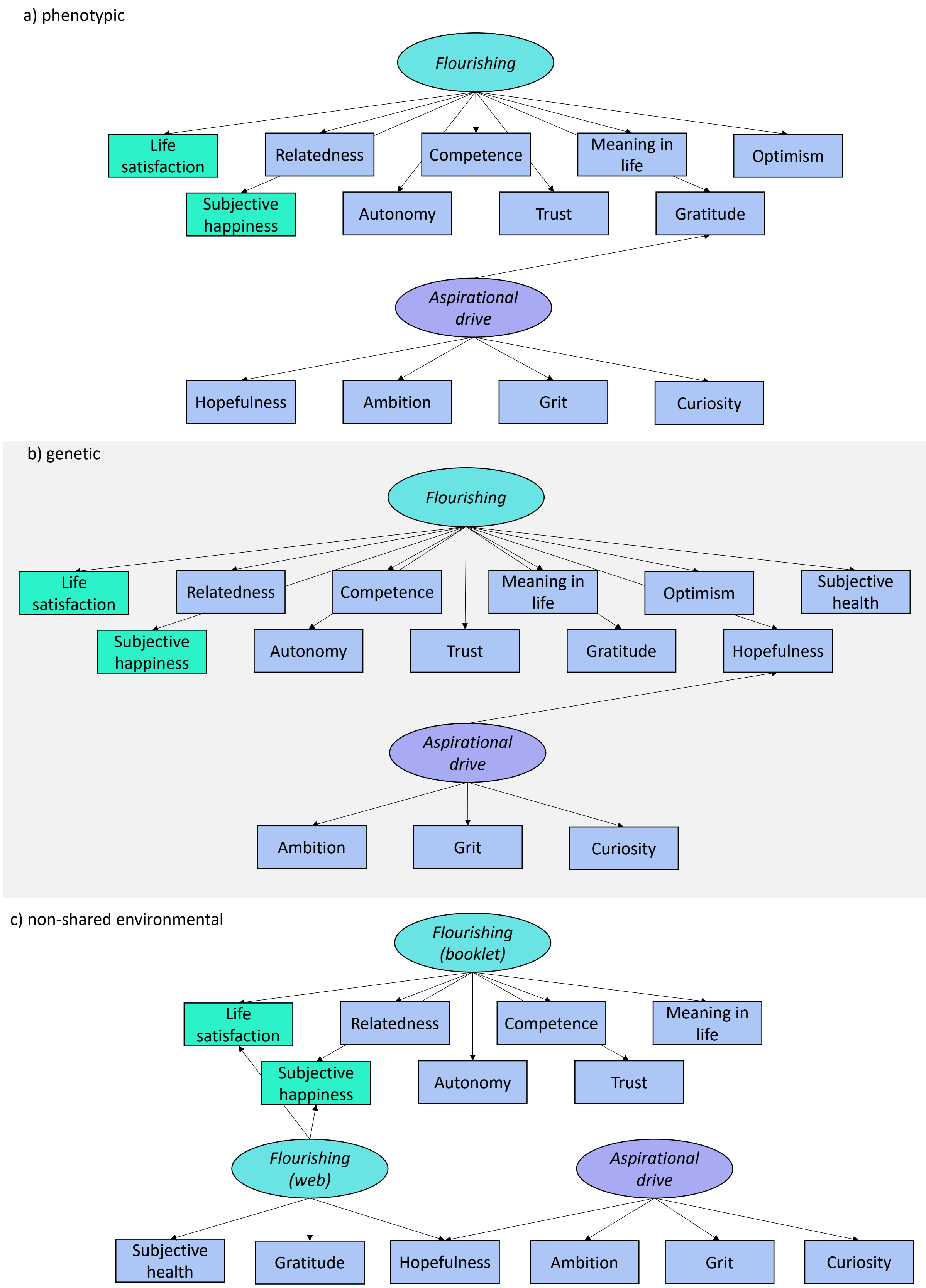


Figure 8.1 Representation of the structure of wellbeing, defined by PCA components from Chapter 4 and Chapter 5. Colour refers to type of wellbeing, where green represents

subjective wellbeing and blue represents eudaimonic wellbeing indicators. a) Wellbeing defined by my *flourishing* and *aspirational drive* components in Chapter 4, where *flourishing* is comprised of multiple subjective wellbeing indicators (life satisfaction and subjective happiness) and multiple eudaimonic wellbeing indicators (relatedness, autonomy, competence, trust, meaning in life, gratitude, optimism) and *aspirational drive* is comprised of multiple eudaimonic wellbeing indicators (hopefulness, ambition, grit and curiosity). b) Wellbeing defined by genetic PCA components in Chapter 5, where *flourishing* is comprised of multiple subjective wellbeing indicators (life satisfaction and subjective happiness) and multiple eudaimonic wellbeing indicators (relatedness, autonomy, competence, trust, meaning in life, gratitude, optimism, hopefulness, subjective health) and *aspirational drive* is defined by multiple eudaimonic wellbeing indicators (hopefulness, ambition, grit and curiosity). c) Wellbeing defined by the nonshared environmental PCA components in Chapter 5, where *flourishing* is defined by two components, first comprised of life satisfaction, subjective happiness, relatedness, autonomy, competence, trust and meaning in life, and second comprised of life satisfaction, subjective happiness, gratitude, hopefulness and subjective health. *Aspirational drive* is comprised of multiple eudaimonic wellbeing indicators (hopefulness, ambition, grit and curiosity).

These estimates are comparable in magnitude with the genetic and nonshared environmental correlations found between subjective wellbeing and depression. Across three studies, the genetic overlap between subjective wellbeing and depressive symptoms in adolescence ranges from -0.53 to -0.76 and the nonshared environmental overlap ranges -0.28 to -0.42 (Bartels, Cacioppo, van Beijsterveldt, & Boomsma, 2013; Baselmans & Bartels, 2018; Haworth, Carter, Eley, & Plomin, 2015). Perhaps there are general genetic effects for mental health, supporting the generalist genes and specific environments hypothesis (Plomin & Kovas, 2005; Trzaskowski, Shakeshaft, & Plomin, 2013). However, no correlations in previous studies or in my thesis are as high as 1, suggesting that there are still genetic and nonshared environmental influences on subjective wellbeing that are independent of the genetic and nonshared environmental influences on depressive symptoms and on eudaimonic wellbeing indicators.

Only one study has explored the relationship between subjective happiness and life satisfaction and depressive symptoms distinctly, finding stronger genetic and nonshared environmental correlations between life satisfaction and depressive symptoms ($rA = -0.73$; $rE = -0.42$) than subjective happiness and depressive symptoms ($rA = -0.53$; $rE = -0.40$). It is interesting that this is the same pattern we observe, where our genetic and nonshared environmental correlations were stronger between life satisfaction and our eudaimonic indicators than between subjective happiness and our eudaimonic wellbeing indicators. This emphasises the need to explore the antecedents, correlates and outcomes of subjective wellbeing using measures of the distinct components of wellbeing.

8.1.2 Identifying the causal relationship between subjective and eudaimonic wellbeing indicators

Though we have identified there is moderate genetic overlap and modest nonshared environmental overlap between subjective wellbeing and eudaimonic wellbeing, we do not yet understand the direction of this relationship. A recent publication explored the relationship between subjective wellbeing and eudaimonic wellbeing in older adults across 30 years, and found eudaimonic wellbeing influenced later subjective wellbeing, but subjective wellbeing had little effect on later eudaimonic wellbeing (Joshanloo, 2018). In adolescence, there is some evidence that eudaimonic traits may be particularly important for individuals with lower subjective wellbeing (Proctor, Linley, & Maltby, 2010). This makes sense from a philosophical position (Waterman, 2013) and it is plausible that eudaimonic wellbeing traits are captured in measures of subjective wellbeing. For example, it is likely that meaning in life, autonomy and competence are considered in cognitive judgements of life satisfaction. However, there is also some evidence that positive affect can influence later experience of eudaimonic traits (King, Hicks, Krull, & Del Gaiso, 2006), though the evidence is mixed (Joshanloo, 2018). We need more evidence of the longitudinal relationship between subjective wellbeing and eudaimonic wellbeing in adolescence to draw strong conclusions.

Few studies have explored the causal relationship between eudaimonic wellbeing and subjective wellbeing using genetically informative designs. Most previous research has aimed to identify the underlying specific genetic and epigenetic influences on subjective wellbeing (Baselmans & Bartels, 2018; Baselmans et al., 2015; Okbay et al., 2016) and my analyses in Chapter 6 have extended this to identify specific environmental influences on both subjective wellbeing and eudaimonic wellbeing. So far, few papers have explored eudaimonic wellbeing, and only one paper has explored the overlap in subjective wellbeing and eudaimonic wellbeing in estimates of genetic variance derived from molecular genetic investigations (Baselmans & Bartels, 2018). Mendelian Randomisation has been used to explore the causal relationship between subjective wellbeing and cardiovascular health (Wootton et al., 2018), but it is likely that the large genetic correlation between subjective wellbeing and eudaimonic wellbeing will mean Mendelian Randomisation is difficult to implement due to pleiotropy (Baselmans & Bartels, 2018). New methods are working towards combining genetically informative methods to strengthen causal inference (Pingault et al., 2018), such as by combining Mendelian randomisation with the direction of causation twin design to identify causal relationships (Minică, Dolan, Boomsma, Geus, & Neale, 2018). However, the sample size required for this method is large (over 2,000 twins) and there are few twin studies with the available data to explore subjective and eudaimonic wellbeing, particularly in adolescence. Therefore it is unlikely we will understand the causal relationship between subjective and eudaimonic wellbeing in adolescence for some time.

8.1.3 The importance of specific nonshared environmental influences to adolescent wellbeing

I have demonstrated that we can use twin studies to identify specific environmental influences that are common to both eudaimonic wellbeing and subjective wellbeing. My analyses in Chapter 6 emphasises the importance of peers for both subjective wellbeing and eudaimonic wellbeing. Though a smaller proportion of the phenotypic correlation is explained by common nonshared environmental overlap in eudaimonic wellbeing and subjective wellbeing (Caprara et al., 2009; Gatt et al., 2014), nonshared environmental influences explain most of the variance within individual wellbeing indicators, as shown in Chapter 5 where on average the nonshared environment explains 57% of the variance in each of our wellbeing indicators. Therefore, it is valuable to identify the specific environmental influences that are shared across wellbeing indicators, and the specific environmental influences that are unique to each indicator.

However, we failed to explain any of the variance in nonshared environmental influences in our wellbeing components, *flourishing* and *aspirational drive*. It is likely that unsystematic nonshared environmental influences account for a large proportion of variance in behavioural traits (Davey Smith, 2011; Turkheimer & Waldron, 2000) and it may be impossible for us to ever identify what is driving these effects by controlled scientific investigation, which is why this problem is often referred to as a 'gloomy prospect' (Plomin & Daniels, 1987; Turkheimer & Waldron, 2000). It may seem daunting that common genetic variants have only small effects on behavioural traits (Haworth & Plomin, 2010), but at least the number of genetic variants in our DNA are finite. The environment defined as anything beyond the DNA sequence (Plomin et al., 2013) creates a more complicated task and we can assume there will be *missing environmentality* in the same way that we see missing heritability.

Even though it may be impossible to identify *all* of the environments that influence behavioural traits, the importance of nonshared environmental influences for many behavioural traits warrants further research. As shown in Chapter 6, we explain up to 24.11% of the nonshared environmental variance in life satisfaction and approximately 5% of the total variance in our subjective and eudaimonic wellbeing indicators. Further research using MZ twin differences methods within a longitudinal design can help identify additional specific environmental influences, which is the best approach when randomised control trials are not possible (Singham et al., 2017). The use of multiple-informant, multiple-scale measures will also help to account for and reduce measurement error. However, few twin datasets have multiple-scale or multiple-informant wellbeing measures during childhood and adolescence. I hope that as wellbeing becomes an increasingly popular topic, more twin datasets will measure wellbeing during childhood so that we can better understand the importance of specific nonshared environmental influences on adolescent wellbeing.

8.1.4 Implications for wellbeing interventions

As described in epidemiology and somatic medicine (Baselmans et al., 2018; Rose, Khaw, & Marmot, 2008), a small shift in the mean distribution of wellbeing at a population level could have large benefits to public health. It is possible that wellbeing contributes to a broader profile of psychological resilience (Diener & Chan, 2011) and increases in wellbeing could protect against the onset of mental health problems (Baselmans et al., 2018). Designing wellbeing interventions for adolescence is incredibly important because they can be implemented at a population level through school settings. School settings are ideal for delivering interventions at a population level and are the last institution all communities have in common (Richardson & Juszczak, 2008). Creating mentally healthy adolescents is likely to result in a mentally healthier adult population (Coffey, Warren, & Gottfried, 2014), which is our best chance at preventing negative mental health outcomes and low wellbeing rather than trying to act after the onset of low wellbeing.

The overlap between subjective wellbeing and eudaimonic wellbeing indicates that interventions targeting eudaimonic wellbeing may improve subjective wellbeing. Most positive interventions target affect or aspects of eudaimonic wellbeing such as gratitude, mindfulness and hope (Bolier et al., 2013; Sin & Lyubomirsky, 2009). A recent meta-analysis of randomised control trials showed that eudaimonic wellbeing interventions, including doing acts of kindness and writing about positive experiences, are effective at improving subjective wellbeing and psychological wellbeing (Bolier et al., 2013). However, these effects were generally small (standardised mean differences of 0.34 for subjective wellbeing, 0.20 for psychological wellbeing and 0.23 for depression), and more immediate than long lasting (Bolier et al., 2013). As the genetic overlap between subjective wellbeing and eudaimonic wellbeing is moderate but not complete, we would expect some interventions to improve both subjective wellbeing and eudaimonic wellbeing, but other interventions to only affect eudaimonic wellbeing in the same way that some, but not all, wellbeing interventions improve negative mental health outcomes (Bolier et al., 2013; Sin & Lyubomirsky, 2009). We need further research to identify effective wellbeing interventions for both subjective and eudaimonic wellbeing in adolescence.

My research can inform the design of such interventions. Across chapters 4 and 5, I found that the basic psychological needs (autonomy, competence and relatedness) were the eudaimonic wellbeing indicators most related to subjective wellbeing. These traits also showed large genetic overlap with subjective wellbeing (genetic correlations ranging 0.69 to 0.79), and in Chapter 6 the nonshared environmental influences on the basic psychological needs were similar in magnitude to the nonshared environmental influences on subjective wellbeing. Consequently, interventions designed to improve competence, autonomy and relatedness may be most effective at improving the overarching construct of wellbeing.

Most wellbeing interventions are targeted at improving the eudaimonic wellbeing indicators that are most associated with *flourishing*, such as meaning in life and optimism and gratitude. There may be value in designing interventions that focus on improving wellbeing through targeting *aspirational drive*. The wellbeing indicators that loaded onto *aspirational drive* were associated with cognitive success, including hopefulness, ambition, curiosity and grit. Such traits may be closely related to psychological resilience (Noble & McGrath, 2012). Few school-wide interventions have already been developed to improve resilience and wellbeing simultaneously (Noble & McGrath, 2012). However, we need scientific investigation to understand how wellbeing, and particularly our *aspirational drive* component of wellbeing, is associated with resilience to inform the design of effective interventions.

8.2 Subjective and eudaimonic wellbeing in adolescence

Mean levels of wellbeing tend to vary across the lifespan (Baselmans et al., 2018; Blanchflower & Oswald, 2008), therefore we have focused on one particular age group to reduce variability. Adolescence is a key developmental stage for mental health and adolescent subjective wellbeing is predictive of subjective wellbeing in young adults (Coffey et al., 2014). It is possible that there are unique factors that influence wellbeing in adolescence compared to other life stages. For example, in Chapter 6 we found that peers are a substantial environmental influence on subjective wellbeing and eudaimonic wellbeing indicators. Yet research shows that perceptions of social networks can change dramatically overtime (Wrzus, Hänel, Wagner, & Neyer, 2013) and it is possible that the influence of peers on wellbeing is different across the lifespan.

Furthermore, the relative importance of subjective wellbeing compared with eudaimonic wellbeing may be different in adolescence than in other life stages. There is some evidence subjective wellbeing is more frequently experienced than eudaimonic wellbeing during adolescence (Keyes, 2006) and that younger adolescents are less orientated towards future goals compared to older adolescents and young adults (Steinberg et al., 2009). It is possible that adolescents can make accurate judgements about their level of subjective wellbeing because they have more experience answering questions about their happiness and life satisfaction, but it may be difficult for adolescents to respond accurately to questions about their eudaimonic wellbeing when they are perhaps still developing autonomy and meaning in their lives (McElhaney, Allen, Stephenson, & Hare, 2009; Steger, Oishi, & Kashdan, 2009). To support this, we would expect to observe more measurement error in eudaimonic wellbeing indicators compared to subjective wellbeing indicators, which would result in a larger nonshared environmental component for eudaimonic wellbeing. However, in Chapter 5, I found similar estimates of nonshared environmental influences across all the wellbeing indicators. This could suggest that adolescents' responses are similarly reliable across subjective and eudaimonic wellbeing. However, even though the magnitude of nonshared environmental variance is similar, we are unable to say whether the balance between measurement error and true environmental variance is the same for subjective and eudaimonic wellbeing.

Overall, the relationship between indicators of wellbeing is likely to be unique in adolescence compared to other life stages. Furthermore, the factors that influence wellbeing may have different magnitudes of effect in adolescence compared to other life stages. This could be particularly true for peer relationships.

8.2.1 The importance of peers to subjective and eudaimonic wellbeing indicators in adolescence

A positive relationship between peer attachment and higher subjective wellbeing in adolescence has been established through observational studies (Balluerka, Gorostiaga, Alonso-Arbiol, & Aritzeta, 2016; Oberle, Schonert-Reichl, & Zumbo, 2011) and genetically informative studies show that social support and wellbeing have substantial genetic overlap (Wang, Davis, Wootton, Mottershaw, & Haworth, 2017). Furthermore, negative peer relationships have a negative influence on wellbeing and can increase mental health problems during adolescence (Arseneault, 2017; Arseneault, Bowes, & Shakoor, 2010; Bowes, Joinson, Wolke, & Lewis, 2015; Rigby, 2000). My research in Chapter 6 contributes to our understanding of the importance of peers to adolescent wellbeing in three ways. First, I show that peers are important to both subjective wellbeing and eudaimonic wellbeing with specificity in the magnitude of effect. Peer attachment explained more of the variance in subjective wellbeing (approx. 12%) than eudaimonic wellbeing (4.22%), and more variance in relatedness (7.56%) compared to meaning in life (0.60%). We need to investigate this relationship further to uncover the mechanisms by which peers influence wellbeing.

Second, I show that peer relationships are important to subjective wellbeing and eudaimonic wellbeing indicators beyond the effects of genetic influences. This suggests that an intervention targeted at improving peer attachment could have a positive effect on wellbeing across an adolescent population because this finding cannot be driven by gene-environment interactions. Evaluations of wellbeing interventions at a school level show that they are effective (Ruini et al., 2009; Seligman, Ernst, Gillham, Reivich, & Linkins, 2009; Waters, 2011), though there are as yet no systematic reviews or meta-analyses of positive interventions in school settings. The effectiveness of school-wide interventions focused on peer relationships to improve adolescent wellbeing should be tested using randomised control trials between schools.

Third, I show that peer attachment explains a substantial proportion of variance in subjective and eudaimonic wellbeing contemporaneously and to a lesser extent six months later. This shows that consistent peer attachment is likely important to wellbeing in adolescence, but there are also some longer lasting effects. This may imply that wellbeing interventions focused on peer relationships should provide adolescents with the opportunity to both build and maintain good quality friendships. We need to understand the longitudinal effects of peer attachment on wellbeing and identify the factors that cause the relationship between peer attachment and wellbeing. This could be explored using social network analysis, which has been used to explore happiness in adults (Fowler & Christakis, 2008) but not yet in adolescents. By recording levels of wellbeing and the closeness of friendships within a school throughout an academic year, we could create a social network and explore how wellbeing changes as the social network changes. We also may be able to understand the connection between wellbeing and the choice of friends. This is likely the closest we could get to understanding the effect of changes in social relationships, given that it is impossible to manipulate real life social ties, and unethical to attempt to do this experimentally.

8.2.2 Consideration of gender differences in adolescent wellbeing

In Chapter 1, I discussed previous research that has highlighted possible differences in wellbeing in adolescence across males and females. Specifically, recent reports suggest a decline in wellbeing in females, with adolescent girls now lower in wellbeing than adolescent boys (Bartels et al., 2013; The Children's Society, 2017). There is also some evidence that response to positive interventions, such as mindfulness meditation, are moderated by gender (Kang et al., 2018). However, other studies have found no evidence that gender moderates response to wellbeing interventions including acts of kindness and writing letters of gratitude (Wang et al., 2017) and so far the effect of gender has not been investigated in meta-analyses of positive interventions (Bolier et al., 2013; Sin & Lyubomirsky, 2009). Gender differences have been found for subjective wellbeing indicators (Bartels et al., 2013; The Children's Society, 2017), but gender differences in eudaimonic wellbeing in adolescence have not been explored. In Chapter 3, I showed that there were minimal differences in mean scores across gender within the TEDS sample, across both subjective wellbeing and eudaimonic wellbeing indicators. In Chapter 5, we also saw minimal gender differences in mean scores of *flourishing* and *aspirational drive*. The absence of gender differences in our study compared to other datasets could be due to differences in data collection methods. Where gender differences have been found previously, wellbeing has been measured as satisfaction with appearance (The Children's Society, 2017) or as a global composite of life satisfaction, subjective happiness and quality of life (Bartels et al., 2013). Furthermore, cohort effects due to year of data collection or location could explain differences. Our data were collected in 2011 whereas gender differences have been found in data collected in 2017 (The Children's Society, 2017) and in the Netherlands compared to the UK (Bartels et al., 2013). Finally, the previously reported gender differences are small and though statistical tests show small significant differences (Bartels et al., 2013), the differences may not be meaningful.

However, this does not mean that the underlying mechanisms that influence wellbeing are equal across gender. Two previous studies found that genetic influences are relatively more important in girls (Bartels et al., 2013; Van der Aa, Boomsma, Rebollo-Mesa, Hudziak, & Bartels, 2010), though both studies use the Netherlands Twin Registry which may suggest there is something unique about this sample. Furthermore, there are some differences in the experience of peer relationships across gender (Martin, Fabes, & Hanish, 2018), therefore it is plausible there are gender differences in the effect of peer relationships on wellbeing. Using a longitudinal study of opposite-sex twin pairs, supportive social relationships appear more protective for depression in women than men (Kendler, Myers, & Prescott, 2005). Such an approach could be applied to understand whether the relationship between peers and wellbeing in adolescence differ across gender.

In summary, the effect of various factors on subjective and eudaimonic wellbeing indicators in adolescence is likely to be different in magnitude to different life stages. These factors are also likely to vary across adolescence as a distinct developmental period. I explored wellbeing in adolescence using a sample of 16 year olds, but the adolescence has been defined as from the onset of puberty (10 – 12 years) until the late teens (Arnett, 2007; Sawyer et al., 2012). It will be important to examine the effect of different factors on wellbeing whilst younger adolescents transition into older adolescents, including how wellbeing changes over this life stage.

8.3 General limitations

Some limitations apply across the whole of my thesis including the limitations of self-reports, the interpretations of the findings within the socio-temporal context, and the use of cross-sectional designs.

8.3.1 Reliance on self-reports

All the measures that I used from the Twins Early Development Study were self-reports and suffer from the usual limitations including social desirability (Diener, 1998) and social comparisons (Diener & Fujita, 1997). This is especially an issue for my studies using the twin design because any systematic reporting bias will either be categorised as measurement error, which inflates estimates of nonshared environmental influences, or will inflate genetic estimates if genetically mediated. To overcome this, we could use measures from multiple informants and more objective measures of wellbeing, including experience sampling (Csikszentmihalyi, Larson, & Prescott, 1977; Kahneman, Krueger, Schkade, Schwarz, & Stone, 2004), social media interaction (Schwartz et al., 2016) and physiological measures (Diener, Scollon, & Lucas, 2003). I attempted to overcome the issue with self-reports in Chapter 7 by using objective measures of the physical environment.

It is likely that the future of phenotyping will triangulate a combination of measures rather than solely relying on self-reports. The National Institute of Mental Health's Research Domain Criteria already provides a framework that combines multiple units of measurement to understand mental health problems, including genetics, cells, physiology, behaviours, self-reports and environmental data (Torous, Onnela, & Keshavan, 2017). The advancement of 'digital phenotyping' using new wearable technology may be one way to capture multiple measures beyond self-reports (Raballo, 2018; Torous et al., 2017) and has already been used in research on schizophrenia relapse (Barnett et al., 2018), intervening in addictive behaviours (Ferreri, Bourla, Mouchabac, & Karila, 2018) and the profiling of suicidal thoughts (Kleiman et al., 2018). In the future digital phenotyping may be applied to understanding wellbeing and used to identify subsamples or key temporal points to deliver appropriate interventions.

8.3.2 Limitations of exploratory work with large datasets

My analyses were cross-sectional and therefore it is impossible to establish causality in the relationship between subjective wellbeing and eudaimonic wellbeing indicators as well as with other related factors. New research has begun to assess the relationship between subjective and eudaimonic wellbeing indicators using causal methods including mendelian randomisation and longitudinal designs (Baselmans & Bartels, 2018; Joshanloo, 2018), and it would be useful to apply such methods to adolescent wellbeing if the data were available.

Additionally, when conducting exploratory work with secondary data, it is important to clearly state methodological decisions before data analysis to reduce the replicability crisis we currently face within the social sciences (Open Science Collaboration, 2015). Preregistration can mitigate such problems to an extent, but it is not directly applicable to exploratory analyses with secondary data. Though I did not preregister my analyses, I applied to use the TEDS dataset specifically for each project, which provides some record of the planned analyses. Furthermore, multiple testing is usual with large datasets. Multiple comparisons can be corrected for using Bonferroni or Benjamini-Hochberg procedure, but correcting for multiple testing also increases the likelihood of false negatives. All the research in my thesis is exploratory and it is important to emphasise that statistically significant findings are indicative of interesting relationships to explore in future research but do not alone provide enough evidence to draw strong conclusions. Throughout my thesis I have explicitly concentrated on the magnitude of the effect rather than on significance and the fact my research is exploratory should be considered when interpreting my findings.

Finally, it is possible that our sample is not representative of the general population because the participants are experienced in responding to data collections (Das, Toepoel, & van Soest, 2011; Warren & Halpern-Manners, 2012), or because we use twins not singletons. Though there is little evidence of panel conditioning effects for behavioural traits (Toepoel, Das, & van Soest, 2009), we could investigate this further by collecting data on eudaimonic wellbeing and subjective wellbeing in a different adolescent sample and using item response theory to explore differences in responses to subjective and eudaimonic wellbeing indicators. Twins are generalisable to singletons for personality characteristics (Johnson, Krueger, Bouchard, & McGue, 2002) and mean scores on subjective wellbeing measures are comparable to that of singletons (Wootton, Davis, Mottershaw, Wang, & Haworth, 2017). We therefore assume that twins are representative of the general population in terms of wellbeing.

8.3.3 Generalisation of findings within the socio-economic context

The context in which individuals live influences their wellbeing (Diener, Lucas, & Oishi, 2018). It is therefore important to consider the socio-economic context at the point of data collection and possible cohort effects. There are likely differences in the way the socio-economic context of 2011, when TEDS wellbeing data collection occurred, influenced adolescent's wellbeing compared to the socio-economic context of today. For example, one major difference is changes in the economy, with adolescents in 2011 experiencing the peak of the Great Recession and today's adolescents experiencing economic uncertainty surrounding Brexit (Cribb, Keiller, & Waters, 2018). Our mean estimates for subjective and eudaimonic wellbeing indicators are similar to the means from studies in different decades

(Lyubomirsky & Lepper, 1999; Seligson, Huebner, & Valois, 2003) suggesting that it is possible to generalise our results to contemporary adolescents.

We know that heritability estimates can change across time and context (Davis, Haworth, Lewis, & Plomin, 2012; Haworth & Davis, 2014), so it is important to emphasise that my heritability estimates in Chapter 5 are representative of adolescents only, and results may vary in different birth cohorts and different countries. For example, nonshared environmental factors have more influence on mental health problems in times of greater environmental adversity (Hicks, DiRago, Iacono, & McGue, 2009), which could also be the case for wellbeing indicators. Furthermore, eudaimonic traits may be particularly important for individuals with lower subjective wellbeing (Proctor et al., 2010). This suggests there are specific contexts and specific subsamples of the population that could benefit more from wellbeing interventions than the general population. Research in this area could be particularly important to provide targeted interventions.

8.4 Conclusion

In summary, my thesis is an initial exploration to understand the complex relationship between subjective wellbeing and diverse eudaimonic wellbeing indicators in adolescence. By using multiple positive psychological traits to represent subjective wellbeing and eudaimonic wellbeing, I was able to demonstrate that the theoretical distinction between subjective and eudaimonic wellbeing does not hold empirically in adolescence. This highlighted the need to establish a definition of wellbeing, which will help to identify the antecedents, correlates and outcomes of wellbeing in future work. I have also demonstrated that there are multiple environmental influences on wellbeing indicators in adolescence, which can explain substantial proportions of variance. It is likely there are many environmental influences on wellbeing in adolescence, each with small effects in the same way there are multiple genetic influences with small effects. In this genomic era, we will benefit from more investigation of environmental exposures to explain more of the missing heritability and the missing environmentality of behavioural traits.

References

Abdi, H., & Williams, L. J. (2010). Principal component analysis. *Wiley Interdisciplinary Reviews: Computational Statistics*, *2*(4), 433–459.

Adelman, H. S., Taylor, L., & Nelson, P. (1989). Minors' dissatisfaction with their life circumstances. *Child Psychiatry & Human Development*, *20*(2), 135–147.

Alfonso, V. C., Allison, D. B., Rader, D. E., & Gorman, B. S. (1996). The extended satisfaction with life scale: Development and psychometric properties. *Social Indicators Research*, *38*(3), 275–301.

Allport, G. W. (1961). *Pattern and growth in personality*. Oxford, England: Holt, Reinhart & Winston.

Amoly, E., Dadvand, P., Forns, J., López-Vicente, M., Basagaña, X., Julvez, J., … Sunyer, J. (2014). Green and blue spaces and behavioral development in Barcelona schoolchildren: the BREATHE project. *Environmental Health Perspectives*, *122*(12), 1351.

Andrew, T., Hart, D. J., Snieder, H., de Lange, M., Spector, T. D., & MacGregor, A. J. (2001). Are twins and singletons comparable? A study of disease-related and lifestyle characteristics in adult women. *Twin Research and Human Genetics*, *4*(6), 464–477.

Andrews, F. M., & Withey, S. B. (1976). *Social Indicators of Well-Being: America's Perception of Life Quality*. New York, US: Plenum Press.

Anglim, J., & Grant, S. (2014). Predicting Psychological and Subjective Well-Being from Personality: Incremental Prediction from 30 Facets Over the Big 5. *Journal of Happiness Studies*, 1–22.

Angold, A., Costello, E. J., Messer, S. C., Pickles, A., Winder, F., & Silver, D. (1995). Development of a short questionnaire for use in epidemiological studies of depression in children and adolescents. *International Journal of Methods in Psychiatric Research*, *5*, 237–249.

Annerstedt, M., Östergren, P.-O., Björk, J., Grahn, P., Skärbäck, E., & Währborg, P. (2012). Green qualities in the neighbourhood and mental health–results from a longitudinal cohort study in Southern Sweden. *BMC Public Health*, *12*(1), 337.

Anusic, I., & Schimmack, U. (2016). Stability and change of personality traits, self-esteem, and well-being: Introducing the meta-analytic stability and change model of retest correlations. *Journal of Personality and Social Psychology*, *110*(5), 766–781.

Appleton, J. J., Christenson, S. L., Kim, D., & Reschly, A. L. (2006). Measuring cognitive and psychological engagement: Validation of the Student Engagement Instrument. *Journal of School Psychology*, *44*(5), 427–445.

Archontaki, D., Lewis, G. J., & Bates, T. C. (2013). Genetic influences on psychological well-being: A nationally representative twin study. *Journal of Personality*, *81*(2), 221–230.

Argyle, M., Martin, M., & Crossland, J. (1989). Happiness as a function of personality and social encounters. *Recent Advances in Social Psychology: An International Perspective*, 189–203.

Armsden, G. C., & Greenberg, M. T. (1987). The inventory of parent and peer attachment: Individual differences and their relationship to psychological well-being in adolescence. *Journal of Youth and Adolescence*, *16*(5), 427–454.

Arnett, J. J. (2007). Emerging Adulthood: What Is It, and What Is It Good For? *Child Development Perspectives*, *1*. https://doi.org/10.1111/j.1750-8606.2007.00016.x

Arseneault, L. (2017). Annual Research Review: The persistent and pervasive impact of being bullied in childhood and adolescence: implications for policy and practice. *Journal of Child Psychology and Psychiatry*, *59*(4), 405-421. https://doi.org/10.1111/jcpp.12841

Arseneault, L., Bowes, L., & Shakoor, S. (2010). Bullying victimization in youths and mental health problems: 'Much ado about nothing'? *Psychological Medicine*, *40*(5), 717–729. https://doi.org/10.1017/S0033291709991383

Arslan, G. (2017). Social Exclusion, Social Support and Psychological Wellbeing at School: A Study of Mediation and Moderation Effect. *Child Indicators Research*, 1–22. https://doi.org/10.1007/s12187-017-9451-1

Asbury, K., Almeida, D., Hibel, J., Harlaar, N., & Plomin, R. (2008). Clones in the classroom: A daily diary study of the nonshared environmental relationship between monozygotic twin differences in school experience and achievement. *Twin Research and Human Genetics*, *11*(06), 586–595.

Asbury, K., Dunn, J. F., & Plomin, R. (2006). Birthweight-discordance and differences in early parenting relate to monozygotic twin differences in behaviour problems and academic achievement at age 7. *Developmental Science*, *9*(2). Retrieved from http://onlinelibrary.wiley.com/doi/10.1111/j.1467-7687.2006.00469.x/full

Asbury, K., Moran, N. E., & Plomin, R. (2016). Non-Shared Environmental Influences on Academic Non-Achievement at Age 16: A Qualitative Hypothesis-Generating Monozygotic Twin Differences Study. *AERA Open*, 1–12.

Asbury, K., Moran, N., & Plomin, R. (2017). Do MZ twins have discordant experiences of friendship? A qualitative hypothesis-generating MZ twin differences study. *PLoS One*, *12*(7), e0180521. https://doi.org/10.1371/journal.pone.0180521

Asbury, K., & Plomin, R. (2017). Understanding and Influencing Pupils' Choices as they Prepare to Leave School. Retrieved from http://eprints.whiterose.ac.uk/112011/1/Public_Report_FINAL_FEB.pdf

Astell-Burt, T., Mitchell, R., & Hartig, T. (2014). The association between green space and mental health varies across the lifecourse. A longitudinal study. *Journal of Epidemiology and Community Health*, *68*(6), 578–583.

Aurelius, M. (180AD). *Meditations*. Oxford: Oxford University Press.

Ayorech, Z., Selzam, S., Smith-Woolley, E., Knopik, V. S., Neiderhiser, J. M., DeFries, J. C., & Plomin, R. (2016). Publication Trends Over 55 Years of Behavioral Genetic Research. *Behavior Genetics*, *46*(5), 603–607.

Balluerka, N., Gorostiaga, A., Alonso-Arbiol, I., & Aritzeta, A. (2016). Peer attachment and class emotional intelligence as predictors of adolescents' psychological well-being: A multilevel approach. *Journal of Adolescence*, *53*, 1–9.

Bann, C. M., Kobau, R., Lewis, M. A., Zack, M. M., & Thompson, W. W. (2012). Development and psychometric evaluation of the public health surveillance well-being scale. *Quality of Life Research*, *21*(6), 1031–1043.

Barnett, I., Torous, J., Staples, P., Sandoval, L., Keshavan, M., & Onnela, J.-P. (2018). Relapse prediction in schizophrenia through digital phenotyping: a pilot study. *Neuropsychopharmacology*, *43*(8), 1660–1666. https://doi.org/10.1038/s41386-018-0030-z

Bartels, M. (2015). Genetics of Wellbeing and Its Components Satisfaction with Life, Happiness, and Quality of Life: A Review and Meta-analysis of Heritability Studies. *Behavior Genetics*, *45*(2), 137–156.

Bartels, M., & Boomsma, D. I. (2009). Born to be happy? The etiology of subjective well-being. *Behavior Genetics*, *39*(6), 605–615.

Bartels, M., Cacioppo, J. T., van Beijsterveldt, T. C., & Boomsma, D. I. (2013). Exploring the association between well-being and psychopathology in adolescents. *Behavior Genetics*, *43*(3), 177–190.

Bartels, M., de Moor, M. H. M., van der Aa, N., Boomsma, D. I., & de Geus, E. J. C. (2012). Regular exercise, subjective wellbeing, and internalizing problems in adolescence: Causality or genetic pleiotropy? *Frontiers in Genetics*, *3*(JAN). https://doi.org/10.3389/fgene.2012.00004

Bartels, M., Saviouk, V., De Moor, M. H., Willemsen, G., van Beijsterveldt, T. C., Hottenga, J.-J., … Boomsma, D. I. (2010). Heritability and genome-wide linkage scan of subjective happiness. *Twin Research and Human Genetics*, *13*(2), 135–142.

Bartels, M., Van den Oord, E., Hudziak, J. J., Rietveld, M. J. H., Van Beijsterveldt, C. E. M., & Boomsma, D. I. (2004). Genetic and environmental mechanisms underlying stability and change in problem behaviors at ages 3, 7, 10, and 12. *Developmental Psychology*, *40*(5), 852.

Baselmans, B. M., & Bartels, M. (2018). A genetic perspective on the relationship between eudaimonic -and hedonic well-being. *BioRxiv*, 283036. https://doi.org/10.1101/283036

Baselmans, B. M., Van Dongen, J., Nivard, M. G., Lin, B. D., Zilhão, N. R., Boomsma, D. I., & Bartels, M. (2015). Epigenome-Wide Association Study of Wellbeing. *Twin Research and Human Genetics*, *18*(6), 710–719. https://doi.org/10.1017/thg.2015.85

Baselmans, B. M., Willems, Y., van Beijsterveldt, T., Ligthart, L., WIllemsen, G., Dolan, C. V., … Bartels, M. (2018). Unraveling the genetic and environmental relationship between well-being and depressive symptoms throughout the lifespan. *OpenBaselmans, Bart et Al. "Unraveling the Genetic and Environmental Relationship Between Well-Being and Depressive Symptoms Throughout the Lifespan". PsyArXiv*, *7*.

Beckham, A. S. (1929). Is the negro happy? *The Journal of Abnormal and Social Psychology*, *24*(2), 186-190.

Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: a practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society. Series B (Methodological)*, 289–300.

Bentham, J. (1996). *The collected works of Jeremy Bentham: An introduction to the principles of morals and legislation*. Clarendon Press. Retrieved from https://books.google.co.uk/books?hl=en&lr=&id=qeVFNvlsVH0C&oi=fnd&pg=PR31&dq=I

ntroduction+to+principles+of+morals+and+legislation,&ots=ZKDOfih27m&sig=WTYg70IQoEVfb2ICCyAS_zdZRYc

Bergen, S. E., Gardner, C. O., & Kendler, K. S. (2007). Age-related changes in heritability of behavioral phenotypes over adolescence and young adulthood: a meta-analysis. *Twin Research and Human Genetics*, *10*(3), 423–433.

Bezold, C. P., Banay, R. F., Coull, B. A., Hart, J. E., James, P., Kubzansky, L. D., … Laden, F. (2017). The association between natural environments and depressive symptoms in adolescents living in the United States. *Journal of Adolescent Health*, *62*(4), 488-495.

Biswas-Diener, R., Kashdan, T. B., & King, L. A. (2009). Two traditions of happiness research, not two distinct types of happiness. *The Journal of Positive Psychology*, *4*(3), 208–211.

Bivand, R., Keitt, T., Rowlingson, B., Pebesma, E., Sumner, M., Hijmans, R., … Rundel, C. (2018). *rgdal: Bindings for the 'Geospatial' Data Abstraction Library* (1.3-4). Retrieved from https://CRAN.R-project.org/package=rgdal

Blais, M. A., Lenderking, W. R., Baer, L., deLorell, A., Peets, K., Leahy, L., & Burns, C. (1999). Development and initial validation of a brief mental health outcome measure. *Journal of Personality Assessment*, *73*(3), 359–373.

Blakemore, S.-J., & Choudhury, S. (2006). Development of the adolescent brain: implications for executive function and social cognition. *Journal of Child Psychology and Psychiatry*, *47*(3–4), 296–312.

Blanchflower, D. G., & Oswald, A. J. (2008). Is well-being U-shaped over the life cycle? *Social Science & Medicine*, *66*(8), 1733–1749.

Bolier, L., Haverman, M., Westerhof, G. J., Riper, H., Smit, F., & Bohlmeijer, E. (2013). Positive psychology interventions: a meta-analysis of randomized controlled studies. *BMC Public Health*, *13*(1), 119–139.

Bor, W., Dean, A. J., Najman, J., & Hayatbakhsh, R. (2014). Are child and adolescent mental health problems increasing in the 21st century? A systematic review. *Australian & New Zealand Journal of Psychiatry*, *48*(7), 606–616. https://doi.org/10.1177/0004867414533834

Bouchard, T. J., & Propping, P. (1993). *Twins as a tool of behavioural genetics*. Chichester, UK: John Wiley & Sons.

Bowes, L., Joinson, C., Wolke, D., & Lewis, G. (2015). Peer victimisation during adolescence and its impact on depression in early adulthood: prospective cohort study in the United Kingdom. *Bmj*, *350*, h2469.

Bowes, L., Maughan, B., Caspi, A., Moffitt, T. E., & Arseneault, L. (2010). Families promote emotional and behavioural resilience to bullying: evidence of an environmental effect. *Journal of Child Psychology and Psychiatry*, *51*(7), 809–817. https://doi.org/10.1111/j.1469-7610.2010.02216.x

Bradburn, N. M. (1969). The structure of psychological well-being. Oxford: Aldine.

Bradshaw, J., Keung, A., Rees, G., & Goswami, H. (2011). Children's subjective well-being: International comparative perspectives. *Children and Youth Services Review*, *33*(4), 548–556.

Bradshaw, J., Martorano, B., Natali, L., & de Neubourg, C. (2013). Children's subjective well-being in rich countries. *Child Indicators Research.*, *6*(4), 619–635.

Brancacci, A., & Morel, P.-M. (2007). *Democritus: Science, the Arts, and the Care of the Soul : Proceedings of the International Colloquium on Democritus, Paris, 18-20 September 2003*. BRILL.

Brereton, F., Clinch, J. P., & Ferreira, S. (2008). Happiness, geography and the environment. *Ecological Economics*, *65*(2), 386–396.

Briley, D. A., & Tucker-Drob, E. M. (2017). Comparing the developmental genetics of cognition and personality over the life span. *Journal of Personality*, *85*(1), 51–64.

Brody, G. H., Moore, K., & Glei, D. (1994). Family processes during adolescence as predictors of parent-young adult attitude similarity: A six-year longitudinal analysis. *Family Relations*, 369–373.

Brown, C., & Robinson, W. (2000). The causes and consequences of random and non-random X chromosome inactivation in humans. *Clinical Genetics*, *58*(5), 353–363. https://doi.org/10.1034/j.1399-0004.2000.580504.x

Buhler, C., & Massarik, F. (1968). *The course of human life: A study of goals in the humanistic perspective*. Oxford: Springer.

Burns, R. A., & Machin, M. A. (2009). Investigating the Structural Validity of Ryff's Psychological Well-Being Scales across Two Samples. *Social Indicators Research*, *93*(2), 359–375.

Burt, S. A. (2009). Rethinking environmental contributions to child and adolescent psychopathology: a meta-analysis of shared environmental influences. *Psychological Bulletin*, *135*(4), 608–637. https://doi.org/10.1037/a0015702

Busseri, M. A. (2018). Examining the structure of subjective well-being through meta-analysis of the associations among positive affect, negative affect, and life satisfaction. *Personality and Individual Differences*, *122*, 68–71. https://doi.org/10.1016/j.paid.2017.10.003

Busseri, M. A., & Sadava, S. W. (2011). A Review of the Tripartite Structure of Subjective Well-Being: Implications for Conceptualization, Operationalization, Analysis, and Synthesis. *Personality and Social Psychology Review*, *15*(3), 290–314. https://doi.org/10.1177/1088868310391271

Butler, J., & Kern, M. L. (2016). The PERMA-Profiler: A brief multidimensional measure of flourishing. *International Journal of Wellbeing*, *6*(3), 1–48.

Campbell, A., Converse, P. E., & Rodgers, W. L. (1976). *The quality of American life: Perceptions, evaluations, and satisfactions*. New York: Russell Sage Foundation. Retrieved from https://books.google.co.uk/books?hl=en&lr=&id=h_QWAwAAQBAJ&oi=fnd&pg=PA21&dq=The+quality+of+American+life+campbell&ots=gKIgrBLoEz&sig=-1a0Fe8HUMq8s2nqcPZsJKTVBh8

Caprara, G. V., Fagnani, C., Alessandri, G., Steca, P., Gigantesco, A., Sforza, L. L. C., & Stazi, M. A. (2009). Human optimal functioning: The genetics of positive orientation towards self, life, and the future. *Behavior Genetics*, *39*(3), 277–284. https://doi.org/10.1007/s10519-009-9267-y

Cattell, R. B. (1966). The scree test for the number of factors. *Multivariate Behavioral Research*, *1*(2), 245–276.

Chassell, J. O. (1928). *The experience variables: a study of the variable factors in experience contributing to the formation of personality*. Rochester: Rochester.

Chen, F. F., Jing, Y., Hayes, A., & Lee, J. M. (2013). Two concepts or two approaches? A bifactor analysis of psychological and subjective well-being. *Journal of Happiness Studies*, *14*(3), 1033–1068.

Chu, P. S., Saucier, D. A., & Hafner, E. (2010). Meta-analysis of the relationships between social support and well-being in children and adolescents. *Journal of Social and Clinical Psychology*, *29*(6), 624–645.

Cicero, M. T. (55AD). *The Orations of Marcus Tullius Cicero* (Vol. 2). Bell and daldy.

Clarke, A., Friede, T., Putz, R., Ashdown, J., Martin, S., Blake, A., … Platt, S. (2011). Warwick-Edinburgh Mental Well-being Scale (WEMWBS): validated for teenage school students in England and Scotland. A mixed methods assessment. *BMC Public Health*, *11*(1), 487.

Coffey, J. K., Warren, M. T., & Gottfried, A. W. (2014). Does infant happiness forecast adult life satisfaction? Examining subjective well-being in the first quarter century of life. *Journal of Happiness Studies*, *16*(6), 1401–1421.

Cohen-Cline, H., Turkheimer, E., & Duncan, G. E. (2015). Access to green space, physical activity and mental health: a twin study. *Journal of Epidemiology and Community Health*, *69*(6), 523–529.

Collishaw, S., Maughan, B., Goodman, R., & Pickles, A. (2004). Time trends in adolescent mental health. *Journal of Child Psychology and Psychiatry*, *45*(8), 1350–1362.

Comrey, A. L., & Lee, H. B. (2013). *A first course in factor analysis* (2nd ed.). Psychology Press. Retrieved from https://books.google.co.uk/books?hl=en&lr=&id=RSsVAgAAQBAJ&oi=fnd&pg=PP1&dq=comrey+lee&ots=I3Ifgmnazf&sig=kOJIZIsknpFdttQTQrSVigN4y5I

Conley, D., Rauscher, E., Dawes, C., Magnusson, P. K., & Siegal, M. L. (2013). Heritability and the equal environments assumption: Evidence from multiple samples of misclassified twins. *Behavior Genetics*, *43*(5), 415–426.

Cooke, P. J., Melchert, T. P., & Connor, K. (2016). Measuring well-being: A review of instruments. *The Counseling Psychologist*, *44*(5), 730–757.

Copeland, E. P., Nelson, R. B., & Traughber, M. C. (2010). Wellness Dimensions Relate to Happiness in Children and Adolescents. *Advances in School Mental Health Promotion*, *3*(4), 25–37. https://doi.org/10.1080/1754730X.2010.9715689

Costello, A., & Osborne, J. (2005). Best practices in exploratory factor analysis: four recommendations for getting the most from your analysis. *Practical Assessment, Research & Evaluation*, *10*(7), 1–9.

CRESH. (2010). UK ward-level green space estimates. *CRESH*. Retrieved from https://cresh.org.uk/cresh-themes/green-spaces-and-health/ward-level-green-space-estimates/

Cribb, J., Keiller, A. N., & Waters, T. (2018). Living standards, poverty and inequality in the UK: 2018. Retrieved from https://www.ifs.org.uk/uploads/R145%20for%20web.pdf

Cripps, K., & Zyromski, B. (2009). Adolescents' psychological well-being and perceived parental involvement: Implications for parental involvement in middle schools. *RMLE Online*, *33*(4), 1–13.

Csikszentmihalyi, M. (2003). Legs or wings? A reply to RS Lazarus. *Psychological Inquiry*, *14*(2), 113–115.

Csikszentmihalyi, M., & Csikszentmihalyi, I. S. (1992). *Optimal experience: Psychological studies of flow in consciousness*. Cambridge university press. Retrieved from https://books.google.co.uk/books?hl=en&lr=&id=tdHLCgAAQBAJ&oi=fnd&pg=PP1&dq=Optimal+experience:+Psychological+studies+of+flow+in+consciousness&ots=EShr23IaQe&sig=T4uhiqCw8xiXN_SZPof3wYKFmlI

Csikszentmihalyi, M., Larson, R., & Prescott, S. (1977). The ecology of adolescent activity and experience. *Journal of Youth and Adolescence*, *6*(3), 281–294.

Cummins, R. A., & Lau, A. (2005). Personal wellbeing index–school children. *Victoria: Deakin University*. Retrieved from http://www.acqol.com.au/iwbg/wellbeing-index/pwi-sc-chinese-cantonese.pdf

Czyz, W., & Ramagopalan, S. V. (2013). Molecular Genetic Causes of Discordance in Monozygotic Twins. *ELS*. https://doi.org/10.1002/9780470015902.a0025033

Darwin, C. (1859). *On the origin of species by means of natural selection, or, the preservation of favoured races in the struggle for life*. London: J. Murray.

Das, M., Toepoel, V., & van Soest, A. (2011). Nonparametric tests of panel conditioning and attrition bias in panel surveys. *Sociological Methods & Research*, *40*(1), 32–56.

Data Science Lab. (2015). ScenicOrNot. *ScenicOrNot*. Retrieved from http://scenicornot.datasciencelab.co.uk

Davey Smith, G. (2011). Epidemiology, epigenetics and the 'Gloomy Prospect': embracing randomness in population health research and practice. *International Journal of Epidemiology*, *40*(3), 537–562.

Davey Smith, G., & Ebrahim, S. (2003). 'Mendelian randomization': can genetic epidemiology contribute to understanding environmental determinants of disease? *International Journal of Epidemiology*, *32*(1), 1–22. https://doi.org/10.1093/ije/dyg070

Davidson, L. M., & Demaray, M. K. (2007). Social support as a moderator between victimization and internalizing-externalizing distress from bullying. *School Psychology Review*, *36*(3), 383–405.

Davis, O. S., Band, G., Pirinen, M., Haworth, C. M., Meaburn, E. L., Kovas, Y., … Trzaskowski, M. (2014). The correlation between reading and mathematics ability at age twelve has a substantial genetic component. *Nature Communications*, *5*, 4204.

Davis, O. S., Haworth, C. M. A., & Plomin, R. (2009). Learning abilities and disabilities: Generalist genes in early adolescence. *Cognitive Neuropsychiatry*, *14*(4–5), 312–331. https://doi.org/10.1080/13546800902797106

Davis, O. S., Haworth, C. M., Lewis, C. M., & Plomin, R. (2012). Visual analysis of geocoded twin data puts nature and nurture on the map. *Molecular Psychiatry*, *17*(9), 867–874.

Davis, O. S., & Plomin, R. (2010). Visualizing genetic similarity at the symptom level: The example of learning disabilities. *Behavioral and Brain Sciences*, *33*(2–3), 155–157.

Dawda, D., & Hart, S. D. (2000). Assessing emotional intelligence: Reliability and validity of the Bar-On Emotional Quotient Inventory (EQ-i) in university students. *Personality and Individual Differences*, *28*(4), 797–812.

De Bruin, G. P., & Du Plessis, G. A. (2015). Bifactor Analysis of the Mental Health Continuum—Short Form (MHC—SF). *Psychological Reports*, *116*(2), 438–446.

De Neve, J.-E., Christakis, N. A., Fowler, J. H., & Frey, B. S. (2012). Genes, Economics, and Happiness. *Journal of Neuroscience, Psychology, and Economics*, *5*(4), 193–211. https://doi.org/10.1037/a0030292

Deater–Deckard, K., Dodge, K. A., Bates, J. E., & Pettit, G. S. (1998). Multiple risk factors in the development of externalizing behavior problems: Group and individual differences. *Development and Psychopathology*, *10*(3), 469–493.

Deci, E. L., & Ryan, R. M. (2000). The" what" and" why" of goal pursuits: Human needs and the self-determination of behavior. *Psychological Inquiry*, *11*(4), 227–268.

Delle Fave, A., Brdar, I., Freire, T., Vella-Brodrick, D., & Wissing, M. P. (2011). The eudaimonic and hedonic components of happiness: Qualitative and quantitative findings. *Social Indicators Research*, *100*(2), 185–207.

Denscombe, M. (2000). Social Conditions for Stress: Young People's Experience of Doing GCSEs. *British Educational Research Journal*, *26*(3), 359–374.

Deparment of Transport. (2012). National Travel Survey: 2011 Statistical Release.

Dfarhud, D., Malmir, M., & Khanahmadi, M. (2014). Happiness & Health: The Biological Factors- Systematic Review Article. *Iranian Journal of Public Health*, *43*(11), 1468–1477.

Diaz, D., Horcajo, J., & Blanco Abarca, A. (2009). Development of an Implicit Overall Well-Being Measure Using the Implicit Association Test. *Spanish Journal of Psychology*, *12*(2), 604–617. https://doi.org/10.1017/S1138741600001979

Diener, E. (1984). Subjective well-being. *Psychological Bulletin*, *95*(3), 542–575.

Diener, E. (1998). Subjective well-being and personality. In *Advanced personality* (pp. 311–334). Springer. Retrieved from http://link.springer.com/chapter/10.1007/978-1-4419-8580-4_13

Diener, E., & Chan, M. Y. (2011). Happy people live longer: Subjective well-being contributes to health and longevity. *Applied Psychology: Health and Well-Being*, *3*(1), 1–43.

Diener, E., Diener, M., & Diener, C. (1995). Factors predicting the subjective well-being of nations. *Journal of Personality and Social Psychology*, *69*(5), 851-864.

Diener, E., Emmons, R. A., Larsen, R. J., & Griffin, S. (1985). The satisfaction with life scale. *Journal of Personality Assessment*, *49*(1), 71–75.

Diener, E., & Fujita, F. (1997). Social comparisons and subjective well-being. In B. P. Buunk & F. X. Gibbons (Eds.), *Health, coping, and well-being: Perspectives from social comparison theory* (pp. 329–357). Mahwah, NJ, US: Lawrence Erlbaum Associates Publishers.

Diener, E., & Lucas, R. E. (1999). Personality and Subjective Well-Being. In E. Kahnemon, E. Diener, & N. Schwarz (Eds.), *Well-being: Foundations of hedonic psychology* (pp. 213–229). New York: Russel Sage Foundation.

Diener, E., Lucas, R. E., & Oishi, S. (2018). Advances and Open Questions in the Science of Subjective Well-Being. *Collabra: Psychology*, *4*(1), 15. https://doi.org/10.1525/collabra.115

Diener, E., Ng, W., Harter, J., & Arora, R. (2010). Wealth and happiness across the world: material prosperity predicts life evaluation, whereas psychosocial prosperity predicts positive feeling. *Journal of Personality and Social Psychology*, *99*(1), 52–61.

Diener, E., Oishi, S., & Lucas, R. E. (2003). Personality, culture, and subjective well-being: Emotional and cognitive evaluations of life. *Annual Review of Psychology*, *54*(1), 403–425.

Diener, E., Pressman, S. D., Hunter, J., & Delgadillo-Chase, D. (2017). If, Why, and When Subjective Well-Being Influences Health, and Future Needed Research. *Applied Psychology: Health and Well-Being*, *9*(2), 133–167.

Diener, E., Sapyta, J. J., & Suh, E. (1998). Subjective Well-Being Is Essential to Well-Being. *Psychological Inquiry*, *9*(1), 33-37.

Diener, E., Scollon, C. N., & Lucas, R. E. (2003). The evolving concept of subjective well-being: the multifaceted nature of happiness. *Advances in Cell Aging and Gerontology*, *15*, 187–219.

Diener, E., Suh, E. M., Lucas, R. E., & Smith, H. L. (1999). Subjective well-being: Three decades of progress. *Psychological Bulletin*, *125*(2), 276-302.

Diener, E., Wirtz, D., Biswas-Diener, R., Tov, W., Kim-Prieto, C., Choi, D., & Oishi, S. (2009). New measures of well-being. *Assessing Well-Being*, 247–266.

Diener, E., Wirtz, D., Tov, W., Kim-Prieto, C., Choi, D., Oishi, S., & Biswas-Diener, R. (2010). New well-being measures: Short scales to assess flourishing and positive and negative feelings. *Social Indicators Research*, *97*(2), 143–156.

Dinisman, T., & Ben-Arieh, A. (2016). The Characteristics of Children's Subjective Well-Being. *Social Indicators Research*, *126*(2), 555–569. https://doi.org/10.1007/s11205-015-0921-x

Dirghangi, S., Kahn, G., Laursen, B., Brendgen, M., Vitaro, F., Dionne, G., & Boivin, M. (2015). Co-rumination cultivates anxiety: A genetically informed study of friend influence during early adolescence. *Developmental Psychology*, *51*(4), 564–571. https://doi.org/10.1037/a0038848

Disabato, D. J., Goodman, F. R., Kashdan, T. B., Short, J. L., & Jarden, A. (2016). Different types of well-being? A cross-cultural examination of hedonic and eudaimonic well-being. *Psychological Assessment*, *28*(5), 471–493.

Dobzhansky, T. G. (1964). *Heredity and the Nature of Man*. New York, US: Harcourt, Brace & World. Retrieved from https://repository.library.georgetown.edu/handle/10822/546973

Dolan, P., Kudma, L., & Testoni, S. (2017). Definitions and measures of subjective wellbeing: discussion paper 3. Retrieved from https://www.whatworkswellbeing.org/product/definitions-and-measures-of-subjective-wellbeing-discussion-paper-3/

Doyal, L., & Gough, I. (1984). A theory of human need. *Critical Social Policy*, (4), 6–38.

Duckworth, A. L., Peterson, C., Matthews, M. D., & Kelly, D. R. (2007). Grit: perseverance and passion for long-term goals. *Journal of Personality and Social Psychology*, *92*(6), 1087–1101. https://doi.org/10.1037/0022-3514.92.6.1087

Duckworth, A. L., & Quinn, P. D. (2009). Development and validation of the Short Grit Scale (GRIT–S). *Journal of Personality Assessment*, *91*(2), 166–174.

Dupuy, H. J. (1984). The Psychological General Well-being Index (PGWB). In N. K. Wenger, M. E. Mattson, C. D. Furburg, & J. Elinson (Eds.), *Assessment of quality of life in clinical trials of cardiovascular therapies.* (pp. 170–183). New York: Le Jacq Publishing Inc.

Dweck, C. (2012). *Mindset: How you can fulfil your potential*. London: Hachette UK.

Edbrooke-Childs, J., Deighton, J., & Wolpert, M. (2017). Changes in severity of psychosocial difficulties in adolescents accessing specialist mental healthcare in England (2009–2014). *Journal of Adolescence*, *60*, 47–52. https://doi.org/10.1016/j.adolescence.2017.07.006

Eley, T. C. (1997). General genes: A new theme in developmental psychopathology. *Current Directions in Psychological Science*, *6*(4), 90–95.

Fagnani, C., Medda, E., Alessandri, G., Delfino, D., D'Ippolito, C., Eisenberg, N., & Stazi, M. A. (2017). The genetic architecture of effortful control and its interplay with psychological adjustment in adolescence. *Journal of Research in Personality*, *68*, 5–14. https://doi.org/10.1016/j.jrp.2017.03.003

Falconer, D. S. (1975). *Introduction to quantitative genetics*. Pearson Education India.

Fazio, A. F. (1977). *A concurrent validational study of the NCHS General Well-Being Schedule*. Hyattsville, MD: National Center for Health Statistics.

Felson, J. (2014). What can we learn from twin studies? A comprehensive evaluation of the equal environments assumption. *Social Science Research*, *43*, 184–199. https://doi.org/10.1016/j.ssresearch.2013.10.004

Feng, D., & Baker, L. (1994). Spouse similarity in attitudes, personality, and psychological well-being. *Behavior Genetics*, *24*(4), 357–364.

Feng, X., & Astell-Burt, T. (2017). The relationship between neighbourhood green space and child mental wellbeing depends upon whom you ask: Multilevel evidence from 3083 children aged

12–13 years. *International Journal of Environmental Research and Public Health*, *14*(3), 235.

Fergusson, D. M., McLeod, G. F. H., Horwood, L. J., Swain, N. R., Chapple, S., & Poulton, R. (2015). Life satisfaction and mental health problems (18 to 35 years). *Psychological Medicine*, *45*(11), 2427–2436.

Ferreri, F., Bourla, A., Mouchabac, S., & Karila, L. (2018). e-Addictology: An Overview of New Technologies for Assessing and Intervening in Addictive Behaviors. *Frontiers in Psychiatry*, *9*. https://doi.org/10.3389/fpsyt.2018.00051

Field, A. (2009). *Discovering statistics using SPSS*. London: Sage publications.

Fisher, R. A. (1918). The Correlation Between Relatives on the Supposition of Mendelian Inheritance. *Transactions of the Royal Society of Edinburgh*, *52*(2), 399–433.

Fisher, R. A. (1925). *Statistical methods for research workers*. Genesis Publishing Pvt Ltd.

Flannigan, J. (2005). An evaluation of residents' attitudes to street trees in southwest England. *Arboricultural Journal*, *28*(4), 219–241. https://doi.org/10.1080/03071375.2005.9747428

Fordyce, M. W. (1988). A review of research on the happiness measures: A sixty second index of happiness and mental health. *Social Indicators Research*, *20*(4), 355–381.

Forgeard, M. J., Jayawickreme, E., Kern, M. L., & Seligman, M. E. (2011). Doing the right thing: Measuring wellbeing for public policy. *International Journal of Wellbeing*, *1*(1), 79–106.

Fowler, J. H., & Christakis, N. A. (2008). Dynamic spread of happiness in a large social network: longitudinal analysis over 20 years in the Framingham Heart Study. *BMJ*, *337*, a2338. https://doi.org/10.1136/bmj.a2338

Franz, C. E., Panizzon, M. S., Eaves, L. J., Thompson, W., Lyons, M. J., Jacobson, K. C., … Kremen, W. S. (2012). Genetic and environmental multidimensionality of well-and ill-being in middle aged twin men. *Behavior Genetics*, *42*(4), 579–591.

Furman, W., & Buhrmester, D. (1992). Age and sex differences in perceptions of networks of personal relationships. *Child Development*, *63*(1), 103–115.

Gallup World Poll. (2006). *Gallup.Com*. Retrieved from http://www.gallup.com/services/170945/world-poll.aspx

Galton, F. (1869). *Hereditary genius: An inquiry into its laws and consequences* (Vol. 27). London: Macmillan.

Galton, F. (1876). The history of twins as a criterion of the relative powers of nature and nurture. *The Journal of the Anthropological Institute of Great Britain and Ireland*, *5*, 391–406.

Galton, F. (1883). *Inquiries into Human Faculty and its Development*. London: Macmillan.

Gana, K., Saada, Y., Broc, G., Quintard, B., Amieva, H., & Dartigues, J.-F. (2016). As long as you've got your health: Longitudinal relationships between positive affect and functional health in old age. *Social Science & Medicine*, *150*, 231–238.

Gatt, J. M., Burton, K. L., Schofield, P. R., Bryant, R. A., & Williams, L. M. (2014). The heritability of mental health and wellbeing defined using COMPAS-W, a new composite measure of wellbeing. *Psychiatry Research*, *219*(1), 204–213.

Generaal, E., Timmermans, E. J., Dekkers, J. E. C., Smit, J. H., & Penninx, B. W. J. H. (2018). Not urbanization level but socioeconomic, physical and social neighbourhood characteristics are associated with presence and severity of depressive and anxiety disorders. *Psychological Medicine*, 1–13. https://doi.org/10.1017/S0033291718000612

Geograph. (2005). Retrieved from http://www.geograph.org.uk/

Gigantesco, A., Stazi, M. A., Alessandri, G., Medda, E., Tarolla, E., & Fagnani, C. (2011). Psychological well-being (PWB): a natural life outlook? An Italian twin study on heritability of PWB in young adults. *Psychological Medicine*, *41*(12), 2637–2649.

Goldstein, K. (1951). On emotions: Considerations from the organismic point of view. *Journal of Psychology*, *32*, 37–49.

Goodman, R. (1997). The Strengths and Difficulties Questionnaire: a research note. *Journal of Child Psychology and Psychiatry*, *38*(5), 581–586.

Green, H., McGinnity, Á., Meltzer, H., Ford, T., & Goodman, R. (2004). *Mental health of children and young people in Great Britain, 2004*. Basingstoke, UK: Palgrave Macmillan.

Grube, G. M., & Reeve, C. D. C. (1992). Plato: Republic. *Indianapolis, IN: Hackett*.

Gubbels, J. S., Kremers, S. P., Droomers, M., Hoefnagels, C., Stronks, K., Hosman, C., & de Vries, S. (2016). The impact of greenery on physical activity and mental health of adolescent and adult residents of deprived neighborhoods: a longitudinal study. *Health & Place*, *40*, 153–160.

Gunderson, E., Tsai, A.-L., Selby, J., Caan, B., J Mayer-Davis, E., & Risch, N. (2006). Twins of Mistaken Zygosity (TOMZ): Evidence for Genetic Contributions to Dietary Patterns and Physiologic Traits, *9*(4), 504–549. https://doi.org/10.1375/183242706778025053

Harding, S. D. (1982). Psychological well-being in Great Britain: An evaluation of the Bradburn affect balance scale. *Personality and Individual Differences*, *3*(2), 167–175.

Harmelen, A.-L. van, Kievit, R. A., Ioannidis, K., Neufeld, S., Jones, P. B., Bullmore, E., … Goodyer, I. (2017). Adolescent friendships predict later resilient functioning across psychosocial domains in a healthy community cohort. *Psychological Medicine*, *47*(13), 2312–2322. https://doi.org/10.1017/S0033291717000836

Harris, J. R. (2011). *The nurture assumption: Why children turn out the way they do*. London: Simon and Schuster.

Hartig, T., Evans, G. W., Jamner, L. D., Davis, D. S., & Gärling, T. (2003). Tracking restoration in natural and urban field settings. *Journal of Environmental Psychology*, *23*(2), 109–123.

Hartman, S. J., Nelson, S. H., & Weiner, L. S. (2018). Patterns of Fitbit Use and Activity Levels Throughout a Physical Activity Intervention: Exploratory Analysis from a Randomized Controlled Trial. *JMIR MHealth and UHealth*, *6*(2). https://doi.org/10.2196/mhealth.8503

Haworth, C. M., Carnell, S., Meaburn, E. L., Davis, O. S., Plomin, R., & Wardle, J. (2008). Increasing heritability of BMI and stronger associations with the FTO gene over childhood. *Obesity*, *16*(12), 2663–2668.

Haworth, C. M., Carter, K., Eley, T. C., & Plomin, R. (2015). Understanding the genetic and environmental specificity and overlap between well-being and internalizing symptoms in adolescence. *Developmental Science*, *20*(2), 1–9. https://doi.org/10.1111/desc.12376

Haworth, C. M., & Davis, O. S. (2014). From observational to dynamic genetics. *Frontiers in Genetics*, *5,* 6. Retrieved from http://www.ncbi.nlm.nih.gov/pmc/articles/PMC3896969/

Haworth, C. M., Davis, O. S., & Plomin, R. (2013). Twins Early Development Study (TEDS): A genetically sensitive investigation of cognitive and behavioral development from childhood to young adulthood. *Twin Research and Human Genetics*, *16*(01), 117–125.

Haworth, C. M., Kovas, Y., Harlaar, N., Hayiou-Thomas, M. E., Petrill, S. A., Dale, P. S., & Plomin, R. (2009). Generalist genes and learning disabilities: a multivariate genetic analysis of low performance in reading, mathematics, language and general cognitive ability in a sample of 8000 12-year-old twins. *Journal of Child Psychology and Psychiatry*, *50*(10), 1318–1325.

Haworth, C. M., Nelson, S. K., Layous, K., Carter, K., Bao, K. J., Lyubomirsky, S., & Plomin, R. (2016). Stability and change in genetic and environmental influences on well-being in response to an intervention. *PLoS ONE*, *11*(5). https://doi.org/10.1371/journal.pone.0155538

Haworth, C. M., & Plomin, R. (2010). Quantitative genetics in the era of molecular genetics: Learning abilities and disabilities as an example. *Journal of the American Academy of Child and Adolescent Psychiatry*, *49*(8), 783–793. https://doi.org/10.1016/j.jaac.2010.01.026

Haworth, C. M., Wright, M. J., Luciano, M., Martin, N. G., De Geus, E. J. C., Van Beijsterveldt, C. E. M., … others. (2010). The heritability of general cognitive ability increases linearly from childhood to young adulthood. *Molecular Psychiatry*, *15*(11), 1112-1120.

Henderson, L. W., & Knight, T. (2012). Integrating the hedonic and eudaimonic perspectives to more comprehensively understand wellbeing and pathways to wellbeing. *International Journal of Wellbeing*, *2*(3), 196-221.

Herle, M., Fildes, A., van Jaarsveld, C., Rijsdijk, F., & Llewellyn, C. H. (2016). Parental Reports of Infant and Child Eating Behaviors are not Affected by Their Beliefs About Their Twins' Zygosity. *Behavior Genetics*, *46*(6), 763–771.

Hervás, G., & Vázquez, C. (2013). Construction and validation of a measure of integrative well-being in seven languages: The Pemberton Happiness Index. *Health and Quality of Life Outcomes*, *11*(1). 66. https://doi.org/10.1186/1477-7525-11-66

Hettema, J. M., Neale, M. C., & Kendler, K. S. (2001). A review and meta-analysis of the genetic epidemiology of anxiety disorders. *American Journal of Psychiatry*, *158*(10), 1568–1578.

Hicks, B. M., DiRago, A. C., Iacono, W. G., & McGue, M. (2009). Gene-Environment Interplay in Internalizing Disorders: Consistent Findings across Six Environmental Risk Factors. *Journal of Child Psychology and Psychiatry, and Allied Disciplines*, *50*(10), 1309–1317. https://doi.org/10.1111/j.1469-7610.2009.02100.x

Hijmans, R. J. (2016). *Spherical Trigonometry* (1.5-5). CRAN.

Hills, P., & Argyle, M. (2002). The Oxford Happiness Questionnaire: A compact scale for the measurement of psychological well-being. *Personality and Individual Differences*, *33*(7), 1073–1082.

Hofmann, R. J. (1978). Complexity and simplicity as objective indices descriptive of factor solutions. *Multivariate Behavioral Research*, *13*(2), 247–250.

Hone, L. C., Jarden, A., Schofield, G., & Duncan, S. (2014). Measuring flourishing: The impact of operational definitions on the prevalence of high levels of wellbeing. *International Journal of Wellbeing*, *4*(1), 62–90.

Horn, J. L. (1965). A rationale and test for the number of factors in factor analysis. *Psychometrika*, *30*(2), 179–185.

Hosang, M., Georgina. (2016). Using smartphone applications to better understand the link between urban design and mental health. *Journal of Urban Design and Mental Health*, *1*, 1-10.

Houlden, V., Weich, S., & Jarvis, S. (2017). A cross-sectional analysis of green space prevalence and mental wellbeing in England. *BMC Public Health*, *17*(1), 460.

Howell, R. T., Kern, M. L., & Lyubomirsky, S. (2007). Health benefits: Meta-analytically determining the impact of well-being on objective health outcomes. *Health Psychology Review*, *1*(1), 83–136.

Hudson, N. W., Lucas, R. E., & Donnellan, M. B. (2017). Day-To-Day Affect is Surprisingly Stable: A 2-Year Longitudinal Study of Well-Being. *Social Psychological and Personality Science*, *8*(1), 45–54. https://doi.org/10.1177/1948550616662129

Huebner, E. S. (1994). Preliminary development and validation of a multidimensional life satisfaction scale for children. *Psychological Assessment*, *6*(2), 149–158.

Huppert, F. A., & So, T. T. (2013). Flourishing across Europe: Application of a new conceptual framework for defining well-being. *Social Indicators Research*, *110*(3), 837–861.

Huta, V. (2016). Eudaimonic and hedonic orientations: Theoretical considerations and research findings. In J. Vittersø (Ed.), *Handbook of Eudaimonic Well-Being* (pp. 215–231). Switzerland: Springer.

International Wellbeing Group. (2013). *Personal Wellbeing Index: 5th Edition*. Melbourne.

Jablonski, W. (1922). Ein Beitrag zur Vererbung der Refraktion menschlicher augener [A contribution to the heredity of refraction in human eyes]. *Arch Augenheilk*, *91*, 308–328.

Jaffee, S., & Price, T. (2007). Gene–environment correlations: a review of the evidence and implications for prevention of mental illness. *Molecular Psychiatry*, *12*(5), 432–442. https://doi.org/10.1038/sj.mp.4001950

Jahoda, M. (1958). *Current concepts of positive mental health.* New York, US: Joint commission on mental health and illness monograph series: Vol. 1. Retrieved from http://doi.apa.org/psycinfo/2006-20880-000

Jang, K. L., McCrae, R. R., Angleitner, A., Riemann, R., & Livesley, W. J. (1998). Heritability of facet-level traits in a cross-cultural twin sample: support for a hierarchical model of personality. *Journal of Personality and Social Psychology*, *74*(6), 1556-1565.

Jasper, H. H. (1930). The measurement of depression-elation and its relation to a measure of extraversion-introversion. *The Journal of Abnormal and Social Psychology*, *25*(3), 307–318.

Johnson, W., & Krueger, R. F. (2006). How money buys happiness: genetic and environmental processes linking finances and life satisfaction. *Journal of Personality and Social Psychology*, *90*(4), 680-691.

Johnson, W., Krueger, R. F., Bouchard, T. J., & McGue, M. (2002). The personalities of twins: Just ordinary folks. *Twin Research and Human Genetics*, *5*(2), 125–131.

Joshanloo, M. (2018). Investigating the relationships between subjective well-being and psychological well-being over two decades. *Emotion*.

Jovanović, V. (2015). A bifactor model of subjective well-being: A re-examination of the structure of subjective well-being. *Personality and Individual Differences*, *87*, 45–49.

Jung, C. G. (1939). *The integration of the personality.* Oxford, England: Farrar & Rinehart.

Kahneman, D., Krueger, A. B., Schkade, D. A., Schwarz, N., & Stone, A. A. (2004). A survey method for characterizing daily life experience: The day reconstruction method. *Science*, *306*(5702), 1776–1780.

Kaiser, H. F. (1958). The varimax criterion for analytic rotation in factor analysis. *Psychometrika*, *23*(3), 187–200.

Kammann, R., & Flett, R. (1983). Affectometer 2: A scale to measure current level of general happiness. *Australian Journal of Psychology*, *35*(2), 259–265.

Kang, Y., Rahrig, H., Eichel, K., Niles, H. F., Rocha, T., Lepp, N. E., … Britton, W. B. (2018). Gender differences in response to a school-based mindfulness training intervention for early adolescents. *Journal of School Psychology*, *68*, 163–176.

Kashdan, T. B., Biswas-Diener, R., & King, L. A. (2008). Reconsidering happiness: The costs of distinguishing between hedonics and eudaimonia. *The Journal of Positive Psychology*, *3*(4), 219–233.

Kashdan, T. B., Rose, P., & Fincham, F. D. (2004). Curiosity and exploration: Facilitating positive subjective experiences and personal growth opportunities. *Journal of Personality Assessment*, *82*(3), 291–305.

Kendler, K. S., & Baker, J. H. (2007). Genetic influences on measures of the environment: a systematic review. *Psychological Medicine*, *37*(5), 615–626. https://doi.org/10.1017/S0033291706009524

Kendler, K. S., & Eaves, L. J. (1986). Models for the joint effect of genotype and environment on liability to psychiatric illness. *The American Journal of Psychiatry*, *143*(3), 279-289.

Kendler, K. S., Myers, J., & Prescott, C. A. (2005). Sex differences in the relationship between social support and risk for major depression: a longitudinal study of opposite-sex twin pairs. *American Journal of Psychiatry*, *162*(2), 250–256.

Kendler, K. S., Neale, M. C., Kessler, R. C., Heath, A. C., & Eaves, L. J. (1992). Major depression and generalized anxiety disorder: same genes,(partly) different environments? *Archives of General Psychiatry*, *49*(9), 716–722.

Kern, M. L., Benson, L., Steinberg, E. A., & Steinberg, L. (2016). The EPOCH Measure of Adolescent Well-Being. *Psychological Assessment*, *28*(5), 586-597.

Kessler, R. C., Amminger, G. P., Aguilar-Gaxiola, S., Alonso, J., Lee, S., & Ustun, T. B. (2007). Age of onset of mental disorders: a review of recent literature. *Current Opinion in Psychiatry*, *20*(4), 359–364.

Keyes, C. L. (2002). The mental health continuum: From languishing to flourishing in life. *Journal of Health and Social Behavior*, 207–222.

Keyes, C. L. (2006). Mental health in adolescence: Is America's youth flourishing?, *76*(3), 395–402. https://doi.org/10.1037/0002-9432.76.3.395

Keyes, C. L. (2009). *Brief description of the mental health continuum short form (MHC-SF)*. Atlanta: Emory University website.

Keyes, C. L., Myers, J. M., & Kendler, K. S. (2010). The Structure of the Genetic and Environmental Influences on Mental Well-Being. *American Journal of Public Health*, *100*(12), 2379–2384.

Keyes, C. L., Shmotkin, D., & Ryff, C. D. (2002). Optimizing well-being: the empirical encounter of two traditions. *Journal of Personality and Social Psychology*, *82*(6), 1007–1022.

Kidger, J., Araya, R., Donovan, J., & Gunnell, D. (2012). The effect of the school environment on the emotional health of adolescents: a systematic review. *Pediatrics*, *129*, 1–25.

Kinderman, P., Schwannauer, M., Pontin, E., & Tai, S. (2011). The development and validation of a general measure of well-being: the BBC well-being scale. *Quality of Life Research*, *20*(7), 1035–1042.

King, L. A., Hicks, J. A., Krull, J. L., & Del Gaiso, A. K. (2006). Positive affect and the experience of meaning in life. *Journal of Personality and Social Psychology*, *90*(1), 179-196.

Kjell, O. N. E., Daukantaitė, D., Hefferon, K., & Sikström, S. (2016). The Harmony in Life Scale Complements the Satisfaction with Life Scale: Expanding the Conceptualization of the

Cognitive Component of Subjective Well-Being. *Social Indicators Research*, *126*(2), 893–919. https://doi.org/10.1007/s11205-015-0903-z

Kleiman, E. M., Turner, B. J., Fedor, S., Beale, E. E., Picard, R. W., Huffman, J. C., & Nock, M. K. (2018). Digital phenotyping of suicidal thoughts. *Depression and Anxiety*, *35*(7), 601–608. https://doi.org/10.1002/da.22730

Klock, A., Clair, A., & Bradshaw, J. (2014). International variation in child subjective well-being. *Child Indicators Research.*, *7*(1), 1–20.

Kovas, Y., Haworth, C. M., Dale, P. S., Plomin, R., Weinberg, R. A., Thomson, J. M., & Fischer, K. W. (2007). *The genetic and environmental origins of learning abilities and disabilities in the early school years* (Vol. 72). Oxford: Blackwell Publishing. Retrieved from http://www.jstor.org/stable/30163178

Krapohl, E., Rimfeld, K., Shakeshaft, N. G., Trzaskowski, M., McMillan, A., Pingault, J.-B., … Plomin, R. (2014). The high heritability of educational achievement reflects many genetically influenced traits, not just intelligence. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(42), 15273–15278. https://doi.org/10.1073/pnas.1408777111

Krekel, C., Kolbe, J., & Wüstemann, H. (2015). The Greener, the Happier? The Effects of Urban Green and Abandoned Areas on Residential Well-Being. *The Effects of Urban Green and Abandoned Areas on Residential Well-Being (January 2015). SOEPpaper*, (728). Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2554477

Kubovy, M. (1999). On the pleasures of the mind. *Well-Being: The Foundations of Hedonic Psychology*, 134–154.

Kuo, F. E., & Faber Taylor, A. (2004). A Potential Natural Treatment for Attention-Deficit/Hyperactivity Disorder: Evidence From a National Study. *American Journal of Public Health*, *94*(9), 1580–1586. https://doi.org/10.2105/AJPH.94.9.1580

Lampe, K. (2014). *The Birth of Hedonism: The Cyrenaic Philosophers and Pleasure as a Way of Life*. Princeton University Press.

Larsen, R. J. (1984). *Theory and measurement of affect intensity as an individual difference characteristic.* ProQuest Information & Learning. Retrieved from http://psycnet.apa.org/psycinfo/1985-53121-001

Larson, L. R., Jennings, V., & Cloutier, S. A. (2016). Public Parks and Wellbeing in Urban Areas of the United States. *PLOS ONE*, *11*(4), e0153211. https://doi.org/10.1371/journal.pone.0153211

Lawlor, M. S., Schonert-Reichl, K. A., Gadermann, A. M., & Zumbo, B. D. (2014). A Validation Study of the Mindful Attention Awareness Scale Adapted for Children. *Mindfulness*, *5*(6), 730–741. https://doi.org/10.1007/s12671-013-0228-4

Layous, K., Chancellor, J., Lyubomirsky, S., Wang, L., & Doraiswamy, P. M. (2011). Delivering happiness: Translating positive psychology intervention research for treating major and minor depressive disorders. *The Journal of Alternative and Complementary Medicine*, *17*(8), 675–683.

Lee, A. C. K., & Maheswaran, R. (2011). The health benefits of urban green spaces: a review of the evidence. *Journal of Public Health*, *33*(2), 212–222. https://doi.org/10.1093/pubmed/fdq068

Lee, S.-W., Ellis, C. D., Kweon, B.-S., & Hong, S.-K. (2008). Relationship between landscape structure and neighborhood satisfaction in urbanized areas. *Landscape and Urban Planning*, *85*(1), 60–70.

Lessof, C., Ross, A., Brind, R., Bell, E., & Newton, S. (2016). Longitudinal Study of Young People in England cohort 2: health and wellbeing at wave 2. *Research Report, Department for Education, Britain.*

Leve, L. D., Harold, G. T., Ge, X., Neiderhiser, J. M., Shaw, D., Scaramella, L. V., & Reiss, D. (2009). Structured parenting of toddlers at high versus low genetic risk: Two pathways to child problems. *Journal of the American Academy of Child & Adolescent Psychiatry*, *48*(11), 1102–1109.

Lewis, A. D., Huebner, E. S., Malone, P. S., & Valois, R. F. (2011). Life satisfaction and student engagement in adolescents. *Journal of Youth and Adolescence*, *40*(3), 249–262.

Liang, H., & Eley, T. C. (2005). A monozygotic twin differences study of nonshared environmental influence on adolescent depressive symptoms. *Child Development*, *76*(6), 1247–1260.

Liew, S. H. M., Elsner, H., Spector, T. D., & Hammond, C. J. (2005). The First 'Classical' Twin Study? Analysis of Refractive Error Using Monozygotic and Dizygotic Twins Published in 1922. *Twin Research and Human Genetics*, *8*(3), 198–200. https://doi.org/10.1375/twin.8.3.198

Lindert, J., Bain, P. A., Kubzansky, L. D., & Stein, C. (2015). Well-being measurement and the WHO health policy Health 2010: Systematic review of measurement scales. *European Journal of Public Health*, *25*(4), 731–740. https://doi.org/10.1093/eurpub/cku193

Linley, P. A., Maltby, J., Wood, A. M., Osborne, G., & Hurling, R. (2009). Measuring happiness: The higher order factor structure of subjective and psychological well-being measures. *Personality and Individual Differences*, *47*(8), 878–884.

Linton, M.-J., Dieppe, P., & Medina-Lara, A. (2016). Review of 99 self-report measures for assessing well-being in adults: exploring dimensions of well-being and developments over time. *BMJ Open*, *6*(7), e010641. https://doi.org/10.1136/bmjopen-2015-010641

Loehlin, J. C. (1996). The Cholesky approach: A cautionary note. *Behavior Genetics*, *26*(1), 65–69.

Lohmann, N. (1977). Correlations of life satisfaction, morale and adjustment measures. *Journal of Gerontology*, *32*(1), 73–75.

Longo, Y., Coyne, I., & Joseph, S. (2017). The scales of general well-being (SGWB). *Personality and Individual Differences*, *109*, 148–159. https://doi.org/10.1016/j.paid.2017.01.005

Longo, Ylenio, Coyne, I., Joseph, S., & Gustavsson, P. (2016). Support for a general factor of well-being. *Personality and Individual Differences*, *100*(Supplement C), 68–72. https://doi.org/10.1016/j.paid.2016.03.082

Lucas, R. E., Diener, E., & Suh, E. (1996). Discriminant validity of well-being measures. *Journal of Personality and Social Psychology*, *71*(3), 616-626.

Lucas, R. E., & Donnellan, M. B. (2012). Estimating the reliability of single-item life satisfaction measures: Results from four national panel studies. *Social Indicators Research*, *105*(3), 323–331.

Lui, P. P., & Fernando, G. A. (2018). Development and Initial Validation of a Multidimensional Scale Assessing Subjective Well-Being: The Well-Being Scale (WeBS). *Psychological Reports*, *121*(1), 135–160. https://doi.org/10.1177/0033294117720696

Lyubomirsky, S., King, L., & Diener, E. (2005). The benefits of frequent positive affect: does happiness lead to success? *Psychological Bulletin*, *131*(6), 803–855.

Lyubomirsky, S., & Lepper, H. S. (1999). A measure of subjective happiness: Preliminary reliability and construct validation. *Social Indicators Research*, *46*(2), 137–155.

Maas, J., Verheij, R. A., Groenewegen, P. P., De Vries, S., & Spreeuwenberg, P. (2006). Green space, urbanity, and health: how strong is the relation? *Journal of Epidemiology and Community Health*, *60*(7), 587–592.

Machin, G. (2009). Non-identical monozygotic twins, intermediate twin types, zygosity testing, and the non-random nature of monozygotic twinning: A review. *American Journal of*

Medical Genetics Part C: Seminars in Medical Genetics, *151C*(2), 110–127. https://doi.org/10.1002/ajmg.c.30212

MacKerron, G., & Mourato, S. (2013). Happiness is greater in natural environments. *Global Environmental Change*, *23*(5), 992–1000.

Manolio, T. A., Collins, F. S., Cox, N. J., Goldstein, D. B., Hindorff, L. A., Hunter, D. J., … Chakravarti, A. (2009). Finding the missing heritability of complex diseases. *Nature*, *461*(7265), 747-753.

Markevych, I., Tiesler, C. M., Fuertes, E., Romanos, M., Dadvand, P., Nieuwenhuijsen, M. J., … Heinrich, J. (2014). Access to urban green spaces and behavioural problems in children: results from the GINIplus and LISAplus studies. *Environment International*, *71*, 29–35.

Markstrom, C. A., Sabino, V. M., Turner, B. J., & Berman, R. C. (1997). The psychosocial inventory of ego strengths: Development and validation of a new Eriksonian measure. *Journal of Youth and Adolescence*, *26*(6), 705–732.

Martin, C. L., Fabes, R. A., & Hanish, L. D. (2018). Differences and similarities: the dynamics of same- and other-sex peer relationships. In W. M. Bukowski, B. Laursen, & K. H. Rubin (Eds.), *Handbook of Peer Interactions, Relationships, and Groups* (pp. 391–409).

Martin, K., Huebner, E. S., & Valois, R. F. (2008). Does life satisfaction predict victimization experiences in adolescence? *Psychology in the Schools*, *45*(8), 705–714. https://doi.org/10.1002/pits.20336

Maslow, A. H. (1968). *Toward a psychology of being*. University of Michigan: Van Nostrand.

Maslow, A. H. (1970). *Motivation and personality*. (L. Carr, Ed.) (Vol. 2). New York, US: Harper & Row.

Maume, D. J. (2013). Social ties and adolescent sleep disruption. *Journal of Health and Social Behavior*, *54*(4), 498–515.

McCrae, R. R., Kurtz, J. E., Yamagata, S., & Terracciano, A. (2011). Internal consistency, retest reliability, and their implications for personality scale validity. *Personality and Social Psychology Review*, *15*(1), 28–50.

McCullough, M. E., Emmons, R. A., & Tsang, J.-A. (2002). The grateful disposition: a conceptual and empirical topography. *Journal of Personality and Social Psychology*, *82*(1), 112–127. https://doi.org/10.1037//0022-3514.82.1.112

McDowell, I. (2010). Measures of self-perceived well-being. *Journal of Psychosomatic Research*, *69*(1), 69–79. https://doi.org/10.1016/j.jpsychores.2009.07.002

McElhaney, K. B., Allen, J. P., Stephenson, J. C., & Hare, A. L. (2009). Attachment and Autonomy During Adolescence. In *Handbook of Adolescent Psychology*. American Cancer Society. https://doi.org/10.1002/9780470479193.adlpsy001012

McKenzie, K., Murray, A., & Booth, T. (2013). Do urban environments increase the risk of anxiety, depression and psychosis? An epidemiological study. *Journal of Affective Disorders*, *150*(3), 1019–1024.

McNair, D., Lorr, M., & Droppleman, L. (1992). Profile of mood states manual (rev.). *San Diego: Educational and Industrial Testing Service*.

Mendel, G. (1965). *Experiments in plant hybridisation*. Cambridge, US: Harvard University Press.

Mental Health Taskforce. (2016). *The five year forward view for mental health*. England. Retrieved from https://www.rcpsych.ac.uk/pdf/The_Five_Year_Forward_View_for_Mental_Health_RCPsych_Policy_Briefing.pdf

Merriman, C. (1924). The intellectual resemblence of twins. *Psychological Monographs*, *33*, 1–58.

Michael, R., Karen, T., Rosemary, G., Kate, N., & Jean, G. (2003). Twins as a natural experiment to study the causes of mild language delay: I: Design; twin–singleton differences in language, and obstetric risks. *Journal of Child Psychology and Psychiatry*, *44*(3), 326–341. https://doi.org/10.1111/1469-7610.00125

Minică, C. C., Dolan, C. V., Boomsma, D. I., Geus, E. de, & Neale, M. C. (2018). Extending Causality Tests with Genetic Instruments: An Integration of Mendelian Randomization with the Classical Twin Design. *Behavior Genetics*, *48*(4), 337–349. https://doi.org/10.1007/s10519-018-9904-4

Moher, D., Liberati, A., Tetzlaff, J., Altman, D. G., & Group, P. (2009). Preferred reporting items for systematic reviews and meta-analyses: the PRISMA statement. *PLoS Medicine*, *6*(7), e1000097.

Morgan, J., & Farsides, T. (2009). Psychometric evaluation of the meaningful life measure. *Journal of Happiness Studies*, *10*(3), 351–366.

Mullins-Sweatt, S. N., Jamerson, J. E., Samuel, D. B., Olson, D. R., & Widiger, T. A. (2006). Psychometric properties of an abbreviated instrument of the five-factor model. *Assessment*, *13*(2), 119–137.

Mynard, H., & Joseph, S. (2000). Development of the multidimensional peer-victimization scale. *Aggressive Behavior*, *26*(2), 169–178.

Neale, M. C., & Cardon, L. (2013). *Methodology for genetic studies of twins and families* (Vol. 67). Springer Science & Business Media. Retrieved from https://books.google.co.uk/books?hl=en&lr=&id=EKYyBwAAQBAJ&oi=fnd&pg=PR13&dq=Neale+%26+Cardon,+2013).&ots=XWUVLtO-ta&sig=buYLb3WoLXT81ywieKEDLDDSLL0

Neale, M. C., Hunter, M. D., Pritikin, J. N., Zahery, M., Brick, T. R., Kirkpatrick, R. M., … Boker, S. M. (2015). OpenMx 2.0: Extended structural equation and statistical modeling. *Psychometrika*, *81*(2), 535–549.

Nes, R. B., Czajkowski, N. O., Røysamb, E., Ørstavik, R. E., Tambs, K., & Reichborn-Kjennerud, T. (2013). Major depression and life satisfaction: a population-based twin study. *Journal of Affective Disorders*, *144*(1), 51–58.

Nes, R. B., Czajkowski, N., & Tambs, K. (2010). Family matters: happiness in nuclear families and twins. *Behavior Genetics*, *40*(5), 577–590.

Nes, R. B., Røysamb, E., Tambs, K., Harris, J. R., & Reichborn-Kjennerud, T. (2006). Subjective well-being: genetic and environmental contributions to stability and change. *Psychological Medicine*, *36*(07), 1033–1042.

NICHD, E. C. C. R. (2005). *Child Care and Child Development: Results from the NICHD Study of Early Child Care and Youth Development*. London: Guilford Press.

Nieboer, A., Lindenberg, S., Boomsma, A., & Bruggen, A. C. V. (2005). Dimensions of well-being and their measurement: the SPF-IL scale. *Social Indicators Research*, *73*(3), 313–353.

Noble, T., & McGrath, H. (2012). Wellbeing and resilience in young people and the role of positive relationships. In S. Roffey (Ed.), *Positive relationships* (pp. 17–33). New York: Springer. Retrieved from http://link.springer.com/chapter/10.1007/978-94-007-2147-0_2

Oberle, E., Schonert-Reichl, K. A., & Zumbo, B. D. (2011). Life satisfaction in early adolescence: Personal, neighborhood, school, family, and peer influences. *Journal of Youth and Adolescence*, *40*(7), 889–901.

O'Connell, B. H., O'Shea, D., & Gallagher, S. (2016). Enhancing social relationships through positive psychology activities: A randomised controlled trial. *The Journal of Positive Psychology*, *11*(2), 149–162.

Odgers, C. L., Caspi, A., Bates, C. J., Sampson, R. J., & Moffitt, T. E. (2012). Systematic social observation of children's neighborhoods using Google Street View: a reliable and cost-effective method. *Journal of Child Psychology and Psychiatry, and Allied Disciplines*, *53*(10), 1009–1017. https://doi.org/10.1111/j.1469-7610.2012.02565.x

Okbay, A., Baselmans, B. M., De Neve, J.-E., Turley, P., Nivard, M. G., Fontana, M. A., … others. (2016). Genetic variants associated with subjective well-being, depressive symptoms, and neuroticism identified through genome-wide analyses. *Nature Genetics*, *48*, 624–633. https://doi.org/10.1038/ng.3552

Oliver, B. R., Pike, A., & Plomin, R. (2008). Nonshared environmental influences on teacher-reported behaviour problems: monozygotic twin differences in perceptions of the classroom. *Journal of Child Psychology and Psychiatry*, *49*(6), 646–653.

Open Science Collaboration. (2015). Estimating the reproducibility of psychological science. *Science*, *349*(6251), aac4716. https://doi.org/10.1126/science.aac4716

Palmore, E., & Kivett, V. (1977). Change in life satisfaction: A longitudinal study of persons aged 46-70. *Journal of Gerontology*, *32*(3), 311–316.

Parackal, M. (2016). A Global Happiness Scale for Measuring Wellbeing: A Test of Immunity Against Hedonism. *Journal of Happiness Studies*, *17*(4), 1529–1545. https://doi.org/10.1007/s10902-015-9657-1

Park, N. (2004). The role of subjective well-being in positive youth development. *The Annals of the American Academy of Political and Social Science*, *591*(1), 25–39.

Pavot, W., Diener, E., & Suh, E. (1998). The temporal satisfaction with life scale. *Journal of Personality Assessment*, *70*(2), 340–354. https://doi.org/10.1207/s15327752jpa7002_11

Peets, K., & Hodges, E. V. E. (2017). Authenticity in friendships and well-being in adolescence. *Social Development*, 1–14. https://doi.org/10.1111/sode.12254

Peterson, C. (2005). *Authentic Happiness Inventory Questionnaire*. Michigan, US: University of Michigan.

Peterson, C., Park, N., & Seligman, M. E. (2005). Orientations to happiness and life satisfaction: The full life versus the empty life. *Journal of Happiness Studies*, *6*(1), 25–41.

Petkus, A. J., Beam, C. R., Johnson, W., Kaprio, J., Korhonen, T., McGue, M., … Consortium, for the I. (2017). Gene–environment interplay in depressive symptoms: moderation by age, sex, and physical illness. *Psychological Medicine*, *47*(10), 1836–1847. https://doi.org/10.1017/S0033291717000290

Petrill, S. A., Plomin, R., DeFries, J. C., & Hewitt, J. K. (Eds.). (2003). *Nature, Nurture, and the Transition to Early Adolescence*. Oxford, New York: Oxford University Press.

Pettersson, E., & Turkheimer, E. (2010). Item selection, evaluation, and simple structure in personality data. *Journal of Research in Personality*, *44*(4), 407–420.

Pingault, J.-B., O'Reilly, P. F., Schoeler, T., Ploubidis, G. B., Rijsdijk, F., & Dudbridge, F. (2018). Using genetic data to strengthen causal inference in observational research. *Nature Reviews Genetics*, 1.

Plomin, R., & Craig, I. (1997). Human behavioural genetics of cognitive abilities and disabilities. *Bioessays*, *19*(12), 1117–1124.

Plomin, R., & Daniels, D. (1987). Why are children in the same family so different from one another? *Behavioral and Brain Sciences*, *10*(01), 1–16.

Plomin, R., & Daniels, D. (2011). Why are children in the same family so different from one another? *International Journal of Epidemiology*, *40*(3), 563–582. https://doi.org/10.1093/ije/dyq148

Plomin, R., DeFries, J. C., Knopik, V. S., & Neiderheiser, J. (2013). *Behavioral genetics* (6th ed.). London: Palgrave Macmillan.

Plomin, R., DeFries, J. C., Knopik, V. S., & Neiderhiser, J. M. (2016). Top 10 replicated findings from behavioral genetics. *Perspectives on Psychological Science*, *11*(1), 3–23.

Plomin, R., Haworth, C. M., & Davis, O. S. (2009). Common disorders are quantitative traits. *Nature Reviews Genetics*, *10*(12), 872–878. https://doi.org/10.1038/nrg2670

Plomin, R., & Kovas, Y. (2005). Generalist genes and learning disabilities. *Psychological Bulletin*, *131*(4), 592–617. https://doi.org/10.1037/0033-2909.131.4.592

Polderman, T. J. C., Benyamin, B., de Leeuw, C. A., Sullivan, P. F., van Bochoven, A., Visscher, P. M., & Posthuma, D. (2015). Meta-analysis of the heritability of human traits based on fifty years of twin studies. *Nature Genetics*, *47*(7), 702–709. https://doi.org/10.1038/ng.3285

Posthuma, D., De Geus, E. J., Bleichrodt, N., & Boomsma, D. I. (2000). Twin–singleton differences in intelligence? *Twin Research and Human Genetics*, *3*(2), 83–87.

Pressman, S. D., & Cohen, S. (2005). Does positive affect influence health? *Psychological Bulletin*, *131*(6), 925–971.

Price, T. S., Freeman, B., Craig, I., Petrill, S. A., Ebersole, L., & Plomin, R. (2000). Infant zygosity can be assigned by parental report questionnaire data. *Twin Research*, *3*(03), 129–133.

Proctor, C., Linley, P. A., & Maltby, J. (2010). Very Happy Youths: Benefits of Very High Life Satisfaction Among Adolescents. *Social Indicators Research*, *98*(3), 519–532. https://doi.org/10.1007/s11205-009-9562-2

Quercia, D., Schifanella, R., & Aiello, L. M. (2014). The shortest path to happiness: Recommending beautiful, quiet, and happy routes in the city. In *Proceedings of the 25th ACM conference on Hypertext and social media* (pp. 116–125).

Raballo, A. (2018). Digital phenotyping: an overarching framework to capture our extended mental states. *The Lancet Psychiatry*, *5*(3), 194–195. https://doi.org/10.1016/S2215-0366(18)30054-3

Ravens-Sieberer, U., Gosch, A., Rajmil, L., Erhart, M., Bruil, J., Power, M., … the KIDSCREEN Group. (2008). The KIDSCREEN-52 Quality of Life Measure for Children and Adolescents: Psychometric Results from a Cross-Cultural Survey in 13 European Countries. *Value in Health*, *11*(4), 645–658. https://doi.org/10.1111/j.1524-4733.2007.00291.x

Reid, C. E., Clougherty, J. E., Shmool, J. L., & Kubzansky, L. D. (2017). Is All Urban Green Space the Same? A Comparison of the Health Benefits of Trees and Grass in New York City. *International Journal of Environmental Research and Public Health*, *14*(11), 1411.

Revelle, W. (2009). *An introduction to psychometric theory with applications in R*.

Revelle, W., & Rocklin, T. (1979). Very simple structure: An alternative procedure for estimating the optimal number of interpretable factors. *Multivariate Behavioral Research*, *14*(4), 403–414.

Revicki, D. A., Leidy, N. K., & Howland, L. (1996). Evaluating the psychometric characteristics of the Psychological General Well-Being Index with a new response scale. *Quality of Life Research*, *5*(4), 419–425.

Richardson, J., & Juszczak, L. (2008). Scools as sites for health-care delivery. *Public Health Reports*, *123*(6), 692–694.

Rigby, K. (2000). Effects of peer victimization in schools and perceived social support on adolescent well-being. *Journal of Adolescence*, *23*(1), 57–68. https://doi.org/10.1006/jado.1999.0289

Rijsdijk, F. V., & Sham, P. C. (2002). Analytic approaches to twin data using structural equation models. *Briefings in Bioinformatics*, *3*(2), 119–133.

Rimfeld, K., Kovas, Y., Dale, P. S., & Plomin, R. (2016). True Grit and Genetics: Predicting Academic Achievement From Personality. *Journal of Personality and Social Psychology*, *Feb 11*, *2016*, No Pagination Specified. http://dx.doi.org/10.1037/pspp0000089

Roeger, L., Allison, S., Martin, G., Dadds, V., & Keeves, J. (2001). Adolescent depressive symptomatology: Improve schools or help students? *Australian Journal of Psychology*, *53*(3), 134–139.

Rogers, C. R. (1946). Significant aspects of client-centered therapy. *American Psychologist*, *1*(10), 415–422.

Rogers, C. R. (1961). *On becoming a person: A therapist's view of psychotherapy*. Boston, US: Houghton Mifflin Harcourt.

Rohrer, J. M., Richter, D., Brümmer, M., Wagner, G. G., & Schmukle, S. C. (2018). Successfully Striving for Happiness: Socially Engaged Pursuits Predict Increases in Life Satisfaction. *Psychological Science*, 956797618761660. https://doi.org/10.1177/0956797618761660

Rose, G., Khaw, K.-T., & Marmot, M. (2008). *Rose's strategy of preventive medicine: the complete original text*. Oxford University Press, USA.

Rose, T., Joe, S., Williams, A., Harris, R., Betz, G., & Stewart-Brown, S. (2017). Measuring Mental Wellbeing Among Adolescents: A Systematic Review of Instruments. *Journal of Child and Family Studies*, *26*(9), 2349–2362. https://doi.org/10.1007/s10826-017-0754-0

Rowe, C. J., & Broadie, S. (2002). *Nicomachean ethics*. New York, US: Oxford University Press.

Røysamb, E., Harris, J. R., Magnus, P., Vittersø, J., & Tambs, K. (2002). Subjective well-being. Sex-specific effects of genetic and environmental factors. *Personality and Individual Differences*, *32*(2), 211–223.

Ruini, C., Ottolini, F., Tomba, E., Belaise, C., Albieri, E., Visani, D., … Fava, G. A. (2009). School intervention for promoting psychological well-being in adolescence. *Journal of Behavior Therapy and Experimental Psychiatry*, *40*(4), 522–532.

Rutter, M., Moffitt, T. E., & Caspi, A. (2006). Gene–environment interplay and psychopathology: Multiple varieties but real effects. *Journal of Child Psychology and Psychiatry*, *47*(3–4), 226–261.

Rutter, M., & Redshaw, J. (1991). Annotation: Growing up as a Twin: Twin-Singleton Differences in Psychological Development. *Journal of Child Psychology and Psychiatry*, *32*(6), 885–895.

Rutter, S. M. J., & Smith, D. J. (Eds.). (1995). *Psychosocial Disorders in Young People: Time Trends and Their Causes* (1 edition). Chichester, West Sussex, England ; New York: Wiley-Blackwell.

Ryan, R. M., Curren, R. R., & Deci, E. L. (2013). What humans need: Flourishing in Aristotelian philosophy and self-determination theory. In A. S. Waterman (Ed.), *The best within us: Positive psychology perspectives on eudaimonia.* Washington, DC, US: American Psychological Association.

Ryan, R. M., & Deci, E. L. (2001). On happiness and human potentials: A review of research on hedonic and eudaimonic well-being. *Annual Review of Psychology*, *52*(1), 141–166.

Ryff, C. D. (1989). Happiness is everything, or is it? Explorations on the meaning of psychological well-being. *Journal of Personality and Social Psychology*, *57*(6), 1069–1081.

Ryff, C. D. (2013). Psychological well-being revisited: Advances in the science and practice of eudaimonia. *Psychotherapy and Psychosomatics*, *83*(1), 10–28.

Ryff, C. D., & Keyes, C. L. (1995). The structure of psychological well-being revisited. *Journal of Personality and Social Psychology*, *69*(4), 719–727.

Ryff, C. D., Singer, B. H., & Love, G. D. (2004). Positive health: connecting well-being with biology. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *359*, 1383–1394.

Sawyer, S. M., Afifi, R. A., Bearinger, L. H., Blakemore, S.-J., Dick, B., Ezeh, A. C., & Patton, G. C. (2012). Adolescence: a foundation for future health. *The Lancet*, *379*(9826), 1630–1640.

Scheier, M. F., Carver, C. S., & Bridges, M. W. (1994). Distinguishing optimism from neuroticism (and trait anxiety, self-mastery, and self-esteem): a reevaluation of the Life Orientation Test. *Journal of Personality and Social Psychology*, *67*(6), 1063–1078.

Schimmack, U., Diener, E., & Oishi, S. (2002). Life-Satisfaction Is a Momentary Judgment and a Stable Personality Characteristic: The Use of Chronically Accessible and Stable Sources. *Journal of Personality*, *70*(3), 345–384. https://doi.org/10.1111/1467-6494.05008

Schwartz, H. A., Sap, M., Kern, M. L., Eichstaedt, J. C., Kapelner, A., Agrawal, M., … Stillwell, D. (2016). Predicting individual well-being through the language of social media. In *Biocomputing 2016: Proceedings of the Pacific Symposium* (pp. 516–527). World Scientific.

Seligman, M. E. (2002). Positive psychology, positive prevention, and positive therapy. *Handbook of Positive Psychology*, *2*, 3–12.

Seligman, M. E. (2012). *Flourish: A new understanding of happiness and well-being*. London: Nicholas Brealey Publishing.

Seligman, M. E., & Csikszentmihalyi, M. (2000). Special issue on happiness, excellence, and optimal human functioning. *American Psychologist*, *55*(1), 5–183.

Seligman, M. E., Ernst, R. M., Gillham, J., Reivich, K., & Linkins, M. (2009). Positive education: Positive psychology and classroom interventions. *Oxford Review of Education*, *35*(3), 293–311.

Seligson, J. L., Huebner, E. S., & Valois, R. F. (2003). Preliminary validation of the brief multidimensional students' life satisfaction scale (BMSLSS). *Social Indicators Research*, *61*(2), 121–145.

Seresinhe, C. I., Preis, T., & Moat, H. S. (2015). Quantifying the Impact of Scenic Environments on Health. *Scientific Reports*, *5*, 16899. https://doi.org/10.1038/srep16899

Seresinhe, C. I., Preis, T., & Moat, H. S. (2017). Using deep learning to quantify the beauty of outdoor places. *Open Science*, *4*(7), 170170.

Settanni, M., & Marengo, D. (2015). Sharing feelings online: studying emotional well-being via automated text analysis of Facebook posts. *Personality and Social Psychology*, *6*, e1045. https://doi.org/10.3389/fpsyg.2015.01045

Sheldon, K. M. (2002). The self-concordance model of healthy goal striving: When personal goals correctly represent the person. In E. L. Deci & R. M. Ryan (Eds.), *Handbook of Self-determination Research* (pp. 65–86). New York, US: University of Rochester Press.

Sheldon, K. M., & Lyubomirsky, S. (2006). Achieving sustainable gains in happiness: Change your actions, not your circumstances. *Journal of Happiness Studies*, *7*(1), 55–86.

Shepherd, J., Oliver, M., & Schofield, G. (2014). Convergent Validity and Test–Retest Reliability of the Authentic Happiness Inventory in Working Adults. *Social Indicators Research*, *124*(3), 1049–1058. https://doi.org/10.1007/s11205-014-0812-6

Siedlecki, K. L., Salthouse, T. A., Oishi, S., & Jeswani, S. (2014). The relationship between social support and subjective well-being across age. *Social Indicators Research*, *117*(2), 561–576.

Silberg, J. L., Copeland, W., Linker, J., Moore, A. A., Roberson-Nay, R., & York, T. P. (2016). Psychiatric outcomes of bullying victimization: a study of discordant monozygotic twins. *Psychological Medicine*, *46*(9), 1875–1883.

Sin, N. L., & Lyubomirsky, S. (2009). Enhancing well-being and alleviating depressive symptoms with positive psychology interventions: A practice-friendly meta-analysis. *Journal of Clinical Psychology*, *65*(5), 467–487.

Singham, T., Viding, E., Schoeler, T., Arseneault, L., Ronald, A., Cecil, C. M., … Pingault, J.-B. (2017). Concurrent and Longitudinal Contribution of Exposure to Bullying in Childhood to Mental Health: The Role of Vulnerability and Resilience. *JAMA Psychiatry*, *74*(11), 1112. https://doi.org/10.1001/jamapsychiatry.2017.2678

Skaff, M. M., Mullan, J. T., Almeida, D. M., Hoffman, L., Masharani, U., Mohr, D., & Fisher, L. (2009). Daily negative mood affects fasting glucose in type 2 diabetes. *Health Psychology*, *28*(3), 265–272.

Skinner, A. L., Stone, C. J., Doughty, H., & Munafò, M. R. (2018). StopWatch: The Preliminary Evaluation of a Smartwatch-Based System for Passive Detection of Cigarette Smoking. *Nicotine & Tobacco Research*. https://doi.org/10.1093/ntr/nty008

Smith, L., Giorgi, S., Solanki, R., Eichstaedt, J., Schwartz, H. A., Abdul-Mageed, M., … Ungar, L. (2016). Does 'well-being'translate on Twitter? In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing* (pp. 2042–2047).

Snyder, C. R., Hoza, B., Pelham, W. E., Rapoff, M., Ware, L., Danovsky, M., … others. (1997). The development and validation of the Children's Hope Scale. *Journal of Pediatric Psychology*, *22*(3), 399–422.

Specht, J., Egloff, B., & Schmukle, S. C. (2013). Examining mechanisms of personality maturation: The impact of life satisfaction on the development of the Big Five personality traits. *Social Psychological and Personality Science*, *4*(2), 181–189.

Springer, K. W., & Hauser, R. M. (2006). An assessment of the construct validity of Ryff's scales of psychological well-being: Method, mode, and measurement effects. *Social Science Research*, *35*(4), 1080–1102.

Springer, K. W., Hauser, R. M., & Freese, J. (2006). Bad news indeed for Ryff's six-factor model of well-being. *Social Science Research*, *35*(4), 1120–1131. https://doi.org/10.1016/j.ssresearch.2006.01.003

Steck, N., Egger, M., Schimmelmann, B. G., Kupferschmid, S., & Cohort, for the S. N. (2018). Suicide in adolescents: findings from the Swiss National cohort. *European Child & Adolescent Psychiatry*, *27*(1), 47–56. https://doi.org/10.1007/s00787-017-1019-6

Steger, M. F., Oishi, S., & Kashdan, T. B. (2009). Meaning in life across the life span: Levels and correlates of meaning in life from emerging adulthood to older adulthood. *The Journal of Positive Psychology*, *4*(1), 43–52. https://doi.org/10.1080/17439760802303127

Steinberg, L., Graham, S., O'Brien, L., Woolard, J., Cauffman, E., & Banich, M. (2009). Age Differences in Future Orientation and Delay Discounting. *Child Development*, *80*(1), 28–44.

Stoolmiller, M. (1999). Implications of the restricted range of family environments for estimates of heritability and nonshared environment in behavior–genetic adoption studies. *Psychological Bulletin*, *125*(4), 392.

Su, R., Tay, L., & Diener, E. (2014). The development and validation of the Comprehensive Inventory of Thriving (CIT) and the Brief Inventory of Thriving (BIT). *Applied Psychology: Health and Well-Being*, *6*(3), 251–279.

Suh, E., Diener, E., Oishi, S., & Triandis, H. C. (1998). The shifting basis of life satisfaction judgments across cultures: Emotions versus norms. *Journal of Personality and Social Psychology*, *74*(2), 482.

Summit, J., & McPherson, E. G. (1998). Residential tree planting and care: A study of attitudes and behavior in Sacramento, California. *Journal of Arboriculture*, *24*(2), 89–97.

Sundquist, K., Frank, G., & Sundquist, J. A. N. (2004). Urbanisation and incidence of psychosis and depression. *The British Journal of Psychiatry*, *184*(4), 293–298.

Tabachnick, B. G., & Fidell, L. S. (2013). *Using Multivariate Statistics* (6th ed.). Boston: Pearson.

Tabachnick, B. G., Fidell, L. S., & others. (2001). *Using multivariate statistics* (5th ed.). New York: Pearson. Retrieved from https://www.ulb.tu-darmstadt.de/tocs/135813948.pdf

Tatarkiewicz, W. (1976). *Analysis of happiness*. The Hague: Martinus Nijhoff.

Tauber, B., Wahl, H.-W., & Schröder, J. (2016). Personality and Life Satisfaction Over 12 Years. *GeroPsych*, *29*(1), 37–48.

Team, R. C. (2016). *R: A language and environment for statistical computing.* Vienna, Austria: R Foundation for Statistical Computing. Retrieved from https://www.R-project.org/

Tennant, R., Hiller, L., Fishwick, R., Platt, S., Joseph, S., Weich, S., … Stewart-Brown, S. (2007). The Warwick-Edinburgh mental well-being scale (WEMWBS): development and UK validation. *Health and Quality of Life Outcomes*, *5*(1), e63.

The Children's Society. (2016). The Good Childhood Report 2016. Retrieved from https://www.childrenssociety.org.uk/what-we-do/resources-and-publications/the-good-childhood-report-2016

The Children's Society. (2017). The Good Childhood Report 2017. Retrieved from https://www.childrenssociety.org.uk/what-we-do/resources-and-publications/the-good-childhood-report-2017

Theis, S. V. S. (1924). *How foster children turn out*. New York, US: State Charities Aid Association.

Toepoel, V., Das, M., & van Soest, A. (2009). Relating question type to panel conditioning: Comparing trained and fresh respondents. In *Survey Research Methods* (Vol. 3, pp. 73–80).

Tomé, G., de Matos, M. G., Camacho, I., Simões, C., & Diniz, J. A. (2014). Friendships Quality and Classmates Support: How to influence the well-being of adolescents. *Higher Education of Social Science*, *7*(2), 149–160.

Torous, J., Onnela, J.-P., & Keshavan, M. (2017). New dimensions and new tools to realize the potential of RDoC: digital phenotyping via smartphones and connected devices. *Translational Psychiatry*, *7*(3), e1053. https://doi.org/10.1038/tp.2017.25

Trzaskowski, M, Yang, J., Visscher, P. M., & Plomin, R. (2014). DNA evidence for strong genetic stability and increasing heritability of intelligence from age 7 to 12. *Molecular Psychiatry*, *19*(3), 380–384. https://doi.org/10.1038/mp.2012.191

Trzaskowski, Maciej, Shakeshaft, N. G., & Plomin, R. (2013). Intelligence indexes generalist genes for cognitive abilities. *Intelligence*, *41*(5), 560–565. https://doi.org/10.1016/j.intell.2013.07.011

Turkheimer, E., & Waldron, M. (2000). Nonshared environment: a theoretical, methodological, and quantitative review. *Psychological Bulletin*, *126*(1), 78–108.

Turley, P., Walters, R. K., Maghzian, O., Okbay, A., Lee, J. J., Fontana, M. A., … Benjamin, D. J. (2017). MTAG: Multi-Trait Analysis of GWAS. *BioRxiv*, 118810. https://doi.org/10.1101/118810

Tuvblad, C., Grann, M., & Lichtenstein, P. (2006). Heritability for adolescent antisocial behavior differs with socioeconomic status: gene–environment interaction. *Journal of Child Psychology and Psychiatry*, *47*(7), 734–743.

van Beijsterveldt, C. E. M., Overbeek, L. I. H., Rozendaal, L., McMaster, M. T. B., Glasner, T. J., Bartels, M., … Boomsma, D. I. (2016). Chorionicity and Heritability Estimates from Twin Studies: The Prenatal Environment of Twins and Their Resemblance Across a Large Number of Traits. *Behavior Genetics*, *46*(3), 304–314. https://doi.org/10.1007/s10519-015-9745-3

Van Dam, N. T., Earleywine, M., & Borders, A. (2010). Measuring mindfulness? An item response theory analysis of the Mindful Attention Awareness Scale. *Personality and Individual Differences*, *49*(7), 805–810.

Van der Aa, N., Boomsma, D. I., Rebollo-Mesa, I., Hudziak, J. J., & Bartels, M. (2010). Moderation of genetic factors by parental divorce in adolescents' evaluations of family functioning and subjective wellbeing. *Twin Research and Human Genetics*, *13*(2), 143–162.

Van Dierendonck, D. (2004). The construct validity of Ryff's Scales of Psychological Well-being and its extension with spiritual well-being. *Personality and Individual Differences*, *36*(3), 629–643.

Van Dillen, S. M., de Vries, S., Groenewegen, P. P., & Spreeuwenberg, P. (2012). Greenspace in urban neighbourhoods and residents' health: adding quality to quantity. *Journal of Epidemiology and Community Health*, *66*(6), e8–e8.

Van't Ent, D., Den Braber, A., Baselmans, B. M., Brouwer, R. M., Dolan, C. V., Hulshoff Pol, H. E., … Bartels, M. (2017). Associations between subjective well-being and subcortical brain volumes. *Scientific Reports*, *7*(1). 6957. https://doi.org/10.1038/s41598-017-07120-z

Velarde, M. D., Fry, G., & Tveit, M. (2007). Health effects of viewing landscapes–Landscape types in environmental psychology. *Urban Forestry & Urban Greening*, *6*(4), 199–212.

Velicer, W. F. (1976). Determining the number of components from the matrix of partial correlations. *Psychometrika*, *41*(3), 321–327.

Verhulst, B. (2017). A Power Calculator for the Classical Twin Design. *Behavior Genetics*, *47*(2), 255–261. https://doi.org/10.1007/s10519-016-9828-9

Viding, E., Fontaine, N. M., Oliver, B. R., & Plomin, R. (2009). Negative parental discipline, conduct problems and callous–unemotional traits: monozygotic twin differences study. *The British Journal of Psychiatry*, *195*(5), 414–419.

Visscher, P. M., Medland, S. E., Ferreira, M. A. R., Morley, K. I., Zhu, G., Cornes, B. K., … Martin, N. G. (2006). Assumption-Free Estimation of Heritability from Genome-Wide Identity-by-Descent Sharing between Full Siblings. *PLOS Genetics*, *2*(3), e41. https://doi.org/10.1371/journal.pgen.0020041

Vittersø, J. (2013). Feelings, meanings, and optimal functioning: Some distinctions between hedonic and eudaimonic well-being. In A. S. Waterman (Ed.), *The best within us: Positive psychology perspectives on eudaimonia.* Washington, DC, US: American Psychological Association.

Vugt, J. M. G. van, & Shulman, L. P. (2006). *Prenatal Medicine*. Taylor & Francis.

Waenerlund, A.-K., Stenmark, H., Bergström, E., Hägglöf, B., Öhman, A., & Petersen, S. (2016). School experiences may be important determinants of mental health problems in middle childhood–a Swedish longitudinal population-based study. *Acta Paediatrica*, *105*(4), 407–415.

Wang, F., Orpana, H. M., Morrison, H., De Groh, M., Dai, S., & Luo, W. (2012). Long-term association between leisure-time physical activity and changes in happiness: Analysis of the prospective National Population Health Survey. *American Journal of Epidemiology*, *176*(12), 1095–1100. https://doi.org/10.1093/aje/kws199

Wang, R. A. H., Davis, O. S. P., Wootton, R. E., Mottershaw, A. L., & Haworth, C. M. (2017). Social support and mental health in late adolescence are correlated for genetic, as well as environmental, reasons. *Scientific Reports*, *7*(1), 13088. https://doi.org/10.1038/s41598-017-13449-2

Warren, J. R., & Halpern-Manners, A. (2012). Panel conditioning in longitudinal social science surveys. *Sociological Methods & Research*, *41*(4), 491–534.

Waterman, A. S. (2008). Reconsidering happiness: A eudaimonist's perspective. *The Journal of Positive Psychology*, *3*(4), 234–252.

Waterman, A. S. (2013a). Introduction: Considering the nature of a life well-lived—Intersections of positive psychology and eudaimonist philosophy. In A. S. Waterman (Ed.). Washington, DC, US: American Psychological Association.

Waterman, A. S. (2013b). *The best within us: Positive psychology perspectives on eudaimonia.* American Psychological Association.

Waterman, A. S., Schwartz, S. J., Zamboanga, B. L., Ravert, R. D., Williams, M. K., Bede Agocha, V., … Brent Donnellan, M. (2010). The Questionnaire for Eudaimonic Well-Being: Psychometric properties, demographic comparisons, and evidence of validity. *The Journal of Positive Psychology*, *5*(1), 41–61.

Waters, L. (2011). A review of school-based positive psychology interventions. *The Australian Educational and Developmental Psychologist*, *28*(02), 75–90.

Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: the PANAS scales. *Journal of Personality and Social Psychology*, *54*(6), 1063-1070.

Wessman, A. E., & Ricks, D. F. (1966). *Mood and personality.* New York, US: Holt, Reinhart & Winston.

Wheeler, B. W., Lovell, R., Higgins, S. L., White, M. P., Alcock, I., Osborne, N. J., … Depledge, M. H. (2015). Beyond greenspace: an ecological study of population general health and indicators of natural environment type and quality. *International Journal of Health Geographics*, *14*(1), 17.

White, M. P., Alcock, I., Wheeler, B. W., & Depledge, M. H. (2013). Would you be happier living in a greener urban area? A fixed-effects analysis of panel data. *Psychological Science*, 0956797612464659.

WHOQOL Group. (1994). The development of the World Health Organisation quality of life assessment instrument (the WHOQOL). In J. Orley & W. Kuyken (Eds.), *Quality of Life Assessment: International Perspectives* (pp. 41–57). Heidelberg: Springer Verlag.

WHOQOL Group. (1998). Development of the World Health Organization WHOQOL-BREF quality of life assessment. *Psychological Medicine*, *28*(3), 551–558.

Williams, M., Coare, P., Marvell, R., Pollard, E., Houghton, A., & Anderson, J. (2015). *Understanding provision for students with mental health problems and intensive support needs*. England: Institute for Employment Studies (IES) and Researching, Equity, Access and Participation (REAP).

Wilson, T. D., & Gilbert, D. T. (2005). Affective Forecasting: Knowing What to Want. *Current Directions in Psychological Science*, *14*(3), 131–134. https://doi.org/10.1111/j.0963-7214.2005.00355.x

Wilson, W. R. (1967). Correlates of avowed happiness. *Psychological Bulletin*, *67*(4), 294–306.

Wold, S., Esbensen, K., & Geladi, P. (1987). Principal component analysis. *Chemometrics and Intelligent Laboratory Systems*, *2*(1), 37–52. https://doi.org/10.1016/0169-7439(87)80084-9

Wood, A., Joseph, S., & Linley, A. (2007). Gratitude-Parent of all virtues. *The Psychologist*, *20*(1), 18-21.

Wood, N. D., Akloubou Gnonhosou, D. C., & Bowling, J. (2015). Combining Parallel and Exploratory Factor Analysis in Identifying Relationship Scales in Secondary Data. *Marriage & Family Review*, *51*(5), 385–395. https://doi.org/10.1080/01494929.2015.1059785

Wootton, R. E., Davis, O. S. P., Mottershaw, A. L., Wang, R. A. H., & Haworth, C. M. (2017). Genetic and environmental correlations between subjective wellbeing and experience of life events in adolescence. *European Child & Adolescent Psychiatry*, *26*(9), 1119–1127. https://doi.org/10.1007/s00787-017-0997-8

Wootton, R. E., Lawn, R. B., Millard, L. A., Davies, N. M., Taylor, A. E., Munafo, M. R., … Haworth, C. M. (2018). Testing the causal effects between subjective wellbeing and physical health using Mendelian randomisation. *BioRxiv*, 304741.

Workum, N., Scholte, R. H., Cillessen, A. H., Lodder, G., & Giletta, M. (2013). Selection, deselection, and socialization processes of happiness in adolescent friendship networks. *Journal of Research on Adolescence*, *23*(3), 563–573.

Wright, S. (1918). On the nature of size factors. *Genetics*, *3*(4), 367-374.

Wright, S. (1921). Correlation and causation. *Journal of Agricultural Research*, *20*(7), 557–585.

Wrzus, C., Hänel, M., Wagner, J., & Neyer, F. J. (2013). Social network changes and life events across the life span: a meta-analysis. *Psychological Bulletin*, *139*(1), 53-80.

Yamagata, S., Takahashi, Y., Ozaki, K., Fujisawa, K. K., Nonaka, K., & Ando, J. (2013). Bidirectional influences between maternal parenting and children’s peer problems: a longitudinal monozygotic twin difference study. *Developmental Science*, *16*(2), 249–259.

Yucel, D., & Yuan, A. S. V. (2016). Parents, Siblings, or Friends? Exploring Life Satisfaction among Early Adolescents. *Applied Research in Quality of Life*, *11*(4), 1399–1423.

Zadow, C., Houghton, S., Hunter, S. C., Rosenberg, M., & Wood, L. (2017). Associations between positive mental well-being and depressive symptoms in Australian adolescents. *The Educational and Developmental Psychologist, 34*(2), 95-105. Retrieved from http://strathprints.strath.ac.uk/60903/

Zhu, Z., Bakshi, A., Vinkhuyzen, A. A., Hemani, G., Lee, S. H., Nolte, I. M., … Milani, L. (2015). Dominance genetic variation contributes little to the missing heritability for human complex traits. *The American Journal of Human Genetics*, *96*(3), 377–385.

Appendices

Appendix 1.1. Search strategy for thecritical review of wellbeing instruments

1.1.1 Search strategy

I performed acritical review to identify instruments that measure hedonic wellbeing, eudaimonic wellbeing, and both hedonic and eudaimonic wellbeing. I followed the methods outlined in the preferred reporting items for systematic reviews and meta-analyses (PRISMA) guidelines (Moher, Liberati, Tetzlaff, Altman, & Group, 2009). The databases searched were Scopus (Elsevier) and Web of Science (Thomas Reuters). The search terms aimed to capture subjective wellbeing included hedonic; affect; feeling; cognitive; life satisfaction (both words within 3 words of each other); mental; and subjective. Eudaimonic wellbeing was searched using eudaimonic; psychological; functioning; purpose; actualisation; meaning. Wellbeing was searched allowing for different spellings, including well being; well-being and wellbeing. To search for validated instruments, I used the terms scale; measure; questionnaire; item; instrument; survey, along with psychometric; reliability; reliable; valid; validity; stability. My searches were limited to English articles, books or book chapters within the past 50 years (1968 to 2018). This was completed in January 2018.

1.1.2 Inclusion and exclusion criteria

The selection criteria were developed on the empirical study record (title and abstract) and then on the instrument level.

Articles

Articles were retained if 1) published within the time frame of 1968-2018; 2) included general population (no illness/clinical/medical population) of adults or adolescents or children; 3) written in English; 4) identified a specific wellbeing measure; 5) was validated or had some assessment of psychometric properties (reliability/validity/stability). Articles were excluded if 1) published outside of time frame; 2) specific population based on illness (illness/clinical/medical population) or age (older adults/elderly/ oldest old/young children under 10); 3) not written in English; 4) did not identify a specific wellbeing measure; 5) focused only on mental illness and did not measure at least one aspect of subjective or eudaimonic wellbeing; 6) did not focus on western culture.

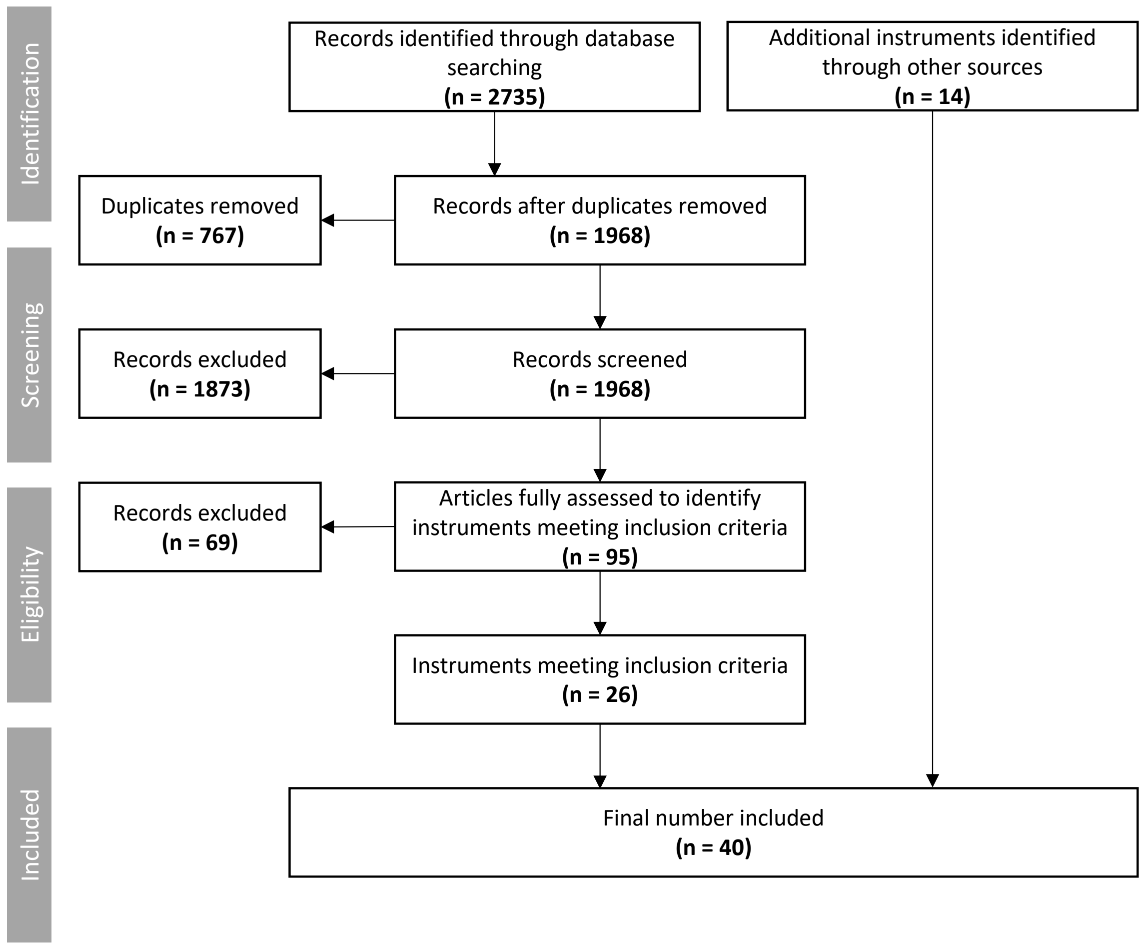
Instruments

Instruments were retained if 1) contained items reflected at least one aspect of subjective or eudaimonic wellbeing. Instruments were excluded if items were not focused on subjective or eudaimonic wellbeing. This included if items 1) were focused on mental illness, or purposely presented mental health as a bipolar scale of wellbeing to mental illness; 2) were focused on quality of life not on wellbeing; 3) focused on general health; 4) focused on resilience; 5) measured physical health; 6) focused on spirituality or religiosity; 7) were not available in English; 8) focused on poor mental health; 9) were context specific (e.g. school, work); 10) were not explicitly referred to as a measure of wellbeing as a standalone instrument; 11) scale was not accessible.

1.1.3 Search results

The initial search identified 1968 records after duplicates had been removed. From the identified records, 95 articles met the inclusion criteria and were screened for a full review.

This resulted in 26 instruments that met the inclusion criteria. A further 14 instruments were identified from other sources, with a total of 40 instruments included in the review. A visual summary of this process is shown in the PRISMA flow diagram below.



Appendix Figure 1.1 PRISMA flow chart of literature search process.

Appendix 1.2 Description of wellbeing instruments identified in the critical literature review, categorised into wellbeing type and subcategorised into wellbeing components

	Wellbeing type	Component	Name of scale (abbreviation)	Author(s) (year)	Traits	Number of items (number of response points)	Reliability estimate	Target population
1.	Subjective	Emotion/affect	Affect Balance Scale	Bradburn (1969)	Positive affect; negative affect; affect balance	5 (2)	Positive affect 0.65; negative affect 0.59[a,1]	General population
2.	Subjective	Emotion/affect	Delighted-Terrible (D-T) Scale	Andrews & Withey (1976)	Emotion	1 (7)	0.66[b]	General population
3.	Subjective	Emotion/affect	Index of General Affect	Campbell, Converse & Rogers (1976)	Positive affect; negative affect	8 (7)	0.89[a]	General population
4.	Subjective	Emotion/affect	Affectometer 2	Kammann & Flett (1983)	Positive experience; negative experience	40 (5)	0.95[a]	General population
5.	Subjective	Emotion/affect	Affect Intensity Measure (AIM)	Larsen (1984)	Positive affect; negative affect; affect intensity	40 (6)	0.89[a,2]	General population
6.	Subjective	Emotion/affect	Positive And Negative Affect Schedule (PANAS)	D. Watson, Clark, & Tellegen (1988)	Positive affect; negative affect	20 (5)	Positive affect 0.88; negative affect 0.87[a]	General population
7.	Subjective	Emotion/affect	Profile of Moods Scale (POMS)	McNair, Lorr, & Droppleman (1992)	1 subscale of positive affect (vigour); 4 subscales of negative affect (depression, anger, fatigue, tension-confusion)	65 (5)	0.63 – 0.96[a]	General population

	Wellbeing type	Component	Name of scale (abbreviation)	Author(s) (year)	Traits	Number of items (number of response points)	Reliability estimate	Target population
8.	Subjective	Emotion/affect	Implicit Overall Wellbeing Measure (IOWBM)	Diaz et al. (2009)	Wellbeing; distress	20 items shown in implicit association task	0.73[a]	General population
9.	Subjective	Emotion/affect	Scale of Positive and Negative Experience (SPANE)	Diener et al. (2010)(2010)	Positive feelings; negative feelings	12 (5)	Positive feelings 0.87; negative feelings 0.81; balance 0.89[a]	General population
10.	Subjective	Emotion/affect	PROMIS Pediatric Positive Affect item bank	Forrest et al. (2017)	Positive affect	Three forms: 39; 8; 4 (5)	0.75; 0.94; 0.92[b]	Children and adolescents
11.	Subjective	Happiness	Happiness Measures (HM)	Fordyce (1988)	Emotional wellbeing by happiness and % of time spent in 'happy', 'unhappy', neutral. Aimed to capture frequency and intensity.	2 (11; 3)	0.62 – 0.98[b]	General population
12.	Subjective	Happiness	Oxford Happiness Inventory (OHI)	Argyle, Martin, & Crossland (1989)	Current level of happiness	29 (4)	0.92[a,3]	General population
13.	Subjective	Happiness	Subjective Happiness Scale (SHS)	Lyubomirsky & Lepper (1999)	General happiness	4 (7)	0.79 – 0.92[a]	General population

	Wellbeing type	Component	Name of scale (abbreviation)	Author(s) (year)	Traits	Number of items (number of response points)	Reliability estimate	Target population
14.	Subjective	Happiness	Authentic Happiness Inventory	Peterson (2005)	Overall happiness. Three domains of the pleasant life; the engaged life; the meaningful life	24 (5)	0.92[b,4]	General population
15.	Subjective	Life/Domain Satisfaction	Satisfaction With Life Scale (SWLS)	Diener, Emmons, Larsen, & Griffin, (1985)	Life Satisfaction	5 (7)	0.87[a]	General population
16.	Subjective	Life/Domain Satisfaction	Perceived Life Satisfaction Scale (PLSS)	Adelman, Taylor, & Nelson (1989)	Dissatisfaction with material and physical wellbeing; relationships; environment; personal development and fulfilment; recreation and entertainment	19 (6)	0.85[b]	Adolescents
17.	Subjective	Life/Domain Satisfaction	Multidimensional Student Life Satisfaction Scale (MSLSS)	Huebner (1994)	Satisfaction with five domains of family; friends; school; living environment; self	40 (4)	Family 0.82; friends 0.85; school 0.85; living environment 0.83; self 0.82; total 0.92[a]	School children
18.	Subjective	Life/Domain Satisfaction	Temporal Satisfaction With Life Scale (TSWLS)	Pavot, Diener, & Suh (1998)	Global life satisfaction (SWLS; Diener et al., 1985) in past, present and future	15 (7)	Past 0.92; present 0.92; future 0.93; total 0.91[a]	General population

	Wellbeing type	Component	Name of scale (abbreviation)	Author(s) (year)	Traits	Number of items (number of response points)	Reliability estimate	Target population
19.	Subjective	Life/Domain Satisfaction	Personal Wellbeing Index, School Children (PWI-A; -SC; -PS; -ID)	International Wellbeing Group (2013)	Satisfaction of life as a whole; eight domains of standard of living; health; life achievement; personal relationships; personal safety; community-connectedness; future security; spirituality-religion	8 (11)	0.84[b,6]	General population (-A = adults; -SC = school-age children and adolescents; -PS = pre-school age children; -ID = intellectual disability or other cognitive impairment)
20.	Subjective	Life/Domain Satisfaction	Harmony In Life Scale (HILS)	Kjell, Daukantaitė, Hefferon, & Sikström (2016)	Psychological balance and flexibility in life	5 (7)	0.77[b]	General population
21.	Eudaimonic	Psychological	Psychological wellbeing (PWB)	Ryff (1989)	Six domains of self-acceptance; positive relations with others; autonomy; environmental mastery; purpose in life; personal growth	20 (6) per domain	Self-acceptance 0.93; positive relations with others 0.91; autonomy 0.86; environmental mastery 0.90; purpose in life 0.90; personal growth 0.87[a]	General population

	Wellbeing type	Component	Name of scale (abbreviation)	Author(s) (year)	Traits	Number of items (number of response points)	Reliability estimate	Target population
22.	Eudaimonic	Psychological	Psychosocial inventory of ego strengths (PIES)	Markstrom et al. (1997)	Eight domains of hope; will; purpose; competence; fidelity; love; care; wisdom	64 (5)	Hope 0.82; will 0.52; purpose 0.78; competence 0.74; fidelity 0.75; love 0.64; care 0.86; wisdom 0.75[a]	General population and adolescents (Markstrom & Marshall, 2007)
23.	Eudaimonic	Psychological	Child and Adolescent Wellness Scale (CAWS)	Copeland et al. (2010), first developed in 2004 (unpublished)	10 components of adaptability; conscientiousness; connectedness; emotional self-regulation; empathy; initiative; mindfulness; optimism; self-efficacy; social competence	150 (4)	Adaptability 0.75; conscientiousness 0.84; connectedness 0.85; emotional self-regulation 0.83; empathy 0.77; initiative 0.77; mindfulness 0.76; optimism 0.86; self-efficacy 0.85; social competence 0.81; total 0.97[a]	Adolescents
24.	Eudaimonic	Self-realisation	Questionnaire for Eudaimonic Wellbeing (QEWB)	Waterman et al. (2010)	Eudaimonic self-realisation; viewed as consequence of having adopted meaningful commitments	21 (5)	0.85 – 0.86[a]	General population

	Wellbeing type	Component	Name of scale (abbreviation)	Author(s) (year)	Traits	Number of items (number of response points)	Reliability estimate	Target population
25.	Subjective and eudaimonic	Hedonic wellbeing and eudaimonic wellbeing	Orientations to Happiness Scale (OTH)	Peterson, Park, & Seligman (2005)	Three domains of life of meaning; life of pleasure; life of engagement	18 (5)	Life of meaning 0.82; life of pleasure 0.82; life of engagement 0.72[a]	General population
26.	Subjective and eudaimonic	Hedonic wellbeing and eudaimonic wellbeing	Warwick-Edinburgh Mental Well-being Scale (WEMWBS)	Tennant et al. (2007)	Positive affect; satisfying interpersonal relationships; positive functioning	14 (5)	0.89 and 0.91[a]	General population
27.	Subjective and eudaimonic	Hedonic wellbeing and eudaimonic wellbeing	Mental Health Continuum Short Form (MHC-SF)	Keyes (2009)	Three domains of emotional wellbeing; psychological wellbeing; social wellbeing	14 (6)	Emotional wellbeing 0.83; psychological wellbeing 0.83; social wellbeing 0.74; total 0.89[a,]	General population
28.	Subjective and eudaimonic	Hedonic wellbeing and eudaimonic wellbeing	Eudaimonic and Hedonic Happiness Investigation instrument (EHHI)	Delle Fave, Brdar, Freire, Vella-Brodrick, & Wissing (2011)	Qualitative aspects of happiness; quantitative evaluation of the degree of happiness and meaningfulness in 11 life domains	8 (6 items open ended; 2 items on 7 points)	*Not available*	General population

	Wellbeing type	Component	Name of scale (abbreviation)	Author(s) (year)	Traits	Number of items (number of response points)	Reliability estimate	Target population
29.	Subjective and eudaimonic	Hedonic wellbeing and eudaimonic wellbeing	Pemberton Happiness Index (PHI)	Hervás & Vázquez (2013)	Remembered wellbeing (general, hedonic, eudaimonic, social); experienced wellbeing (positive and negative emotions)	11 remembered; 10 experienced	0.82 – 0.93[a] across 9 countries	General population
30.	Subjective and eudaimonic	Hedonic wellbeing and eudaimonic wellbeing	Comprehensive Inventory of Thriving	Su, Tay, & Diener (2014)	18 facets of positive functioning representing 7 dimensions of psychological wellbeing (subjective wellbeing, relationship, meaning, engagement, mastery, optimism, autonomy)	54 (5)	0.71 – 0.96[a] across the 18 facets	General population
31.	Subjective and eudaimonic	Hedonic wellbeing and eudaimonic wellbeing	EPOCH Measure of Adolescent Wellbeing	Kern et al. (2016)	5 EPOCH components of Engagement; Perseverance; Optimism; Connectedness; Happiness	20 (5)	Engagement 0.74; perseverance 0.79; optimism 0.76; connectedness 0.77; happiness 0.83; total 0.92[a]	Adolescents

	Wellbeing type	Component	Name of scale (abbreviation)	Author(s) (year)	Traits	Number of items (number of response points)	Reliability estimate	Target population
32.	Subjective and eudaimonic	Hedonic wellbeing and eudaimonic wellbeing	Scales of General Well-Being (SGWB)	Longo et al. (2017)	Fourteen scales of happiness; vitality; calmness; optimism; involvement; self-awareness; self-acceptance; self-worth; competence; development; purpose; significance; self-congruence; connection	65 (7) in total. Items per scale: happiness 4; vitality 4; calmness 4; optimism 5; involvement 4; self-awareness 4; self-acceptance 4; self-worth 5; competence 6; development 5; purpose 5; significance 5; self-congruence 5; connection 5	Happiness 0.77; vitality 0.75; calmness 0.68; optimism 0.86; involvement 0.62; self-awareness 0.58; self-acceptance 0.74; self-worth 0.86; competence 0.76; development 0.65; purpose 0.83; significance 0.75; self-congruence 0.68; connection 0.79; total GWB 0.88[b]	General population
33.	Subjective and eudaimonic	Wellbeing as flourishing	Flourishing Scale (FS)	(Diener et al., 2010)	Positive relationships; competence; meaning and purpose	8 (7)	0.87[a]	General population
34.	Subjective and eudaimonic	Wellbeing as flourishing	Flourishing	Huppert & So (2013)	Ten domains of competence; emotional stability; engagement; meaning; optimism; positive emotion; positive relationships; resilience; self-esteem; vitality	10 (5; positive emotion = 11; emotional stability and vitality = 4)	*Not available*	General population

	Wellbeing type	Component	Name of scale (abbreviation)	Author(s) (year)	Traits	Number of items (number of response points)	Reliability estimate	Target population
35.	Subjective and eudaimonic	Wellbeing as flourishing	COMPAS-W	Gatt, Burton, Schofield, Bryant, & Williams (2014)	Seven domains of Composure; Own-Worth; Mastery; Positivity; Achievement; Satisfaction; Wellbeing	26 (5)	Composure 0.55; Own-Worth 0.69; Mastery 0.71; Positivity 0.69; Achievement 0.72; Satisfaction 0.66; Wellbeing 0.84[a]	General population
36.	Subjective and eudaimonic	General wellbeing	Psychological General Well-Being Index (PGWBI). This is the 22-item version of the GWBS (Fazio, 1977)	Dupuy (1984)	Six HRQoL domains of anxiety; depressed mood; positive wellbeing; self-control; general health; vitality	22 (6)	Anxiety 0.82; depressed mood 0.89; positive wellbeing 0.88; self-control 0.76; general health 0.61; vitality 0.65; total 0.96[a]	General population
37.	Subjective and eudaimonic	General wellbeing	Schwartz Outcomes Scale – 10 (SOS–10)	Blais et al. (1999)	Psychological health	10 (7)	0.96[a]	Clinical and general population
38.	Subjective and eudaimonic	General wellbeing	Social Production Function Instrument for the Level of wellbeing (SPF-IL)	Nieboer et al. (2005)	Five domains of affection; behavioural confirmation; status; comfort; stimulation	64 (4)	Affection 0.79; behavioural confirmation 0.71; status 0.60; comfort 0.86; stimulation 0.79[a]	General population

	Wellbeing type	Component	Name of scale (abbreviation)	Author(s) (year)	Traits	Number of items (number of response points)	Reliability estimate	Target population
39.	Subjective and eudaimonic	General wellbeing	BBC wellbeing-being scale	Kinderman, Schwannauer, Pontin, & Tai (2011)	Three domains of psychological wellbeing; physical health and wellbeing; relationships	24 (4)	Psychological wellbeing 0.93; physical health and wellbeing 0.88; relationships 0.79; total 0.94[a]	General population
40.	Subjective and eudaimonic	General wellbeing	Public Health Surveillance Well-Being Scale (PHS-WB)	Bann, Kobau, Lewis, Zack, & Thompson (2012)	Mental, physical and social components of wellbeing	10 (5)	0.87[a]	General population

Note. Wellbeing type refers to type based on the philosophical and scientific theory discussed at the start of this chapter. Component refers to the specific aspect of the wellbeing type being measured. Traits refers to the individual traits measured by the instrument. Number of response points refers to the number of points on the response scale. Type of reliability estimate is indicated by the superscript letter: [a]Chronbach's Alpha; [b]Test-retest reliability. The superscript number indicates the reference for the reliability estimate, where the reliability estimate was not available in the main reference: [1]Harding (1982); [2](Dawda & Hart, 2000); [3]Hills & Argyle (2002); [4]Shepherd, Oliver, & Schofield, (2014); [5]Palmore & Kivett (1977); [6]Lau & Cummins (2005).

Appendix 1.3 Description of eudaimonic wellbeing components identified in the wellbeing instruments from mycritical literature review

	Eudaimonic wellbeing component	Specific name of eudaimonic wellbeing measure used in the instruments
1.	Self-acceptance	Self-acceptance
2.	Positive relations with others	Positive relations with others; satisfying interpersonal relationships; social wellbeing; social wellbeing; relationships; connection; positive relationships; positive relationships; relationships; social wellbeing; connectedness; connectedness; social competence
3.	Autonomy	Autonomy
4.	Environmental mastery	Environmental mastery ; competence; mastery; competence; competence; competence; mastery
5.	Purpose in life	Purpose in life; purpose; life of meaning; meaningfulness; meaning; purpose; meaning and purpose; meaning;
6.	Personal growth	Personal growth; development
7.	Hope	Hope
8.	Will	Will
9.	Fidelity	Fidelity
10.	Love	Love
11.	Care	Care
12.	Wisdom	Wisdom
13.	Self-realisation	Self-realisation
14.	Life of pleasure	Life of pleasure
15.	Life of engagement	Life of engagement; engagement; engagement
16.	Positive functioning	Positive functioning; psychological wellbeing; eudaimonic wellbeing; psychological wellbeing;
17.	Optimism	Optimism; optimism; optimism
18.	Vitality	Vitality; vitality
19.	Calmness	Calmness
20.	Involvement	Involvement
21.	Self-awareness	Self-awareness; self-control; self-regulation; mindfulness

	Eudaimonic wellbeing component	Specific name of eudaimonic wellbeing measure used in the instruments
22.	Self-worth	Self-worth; significance; own-worth
23.	Self-congruence	Self-congruence; self-efficacy
24.	Emotional stability	Emotional stability
25.	Resilience	Resilience; adaptability; perseverance
26.	Self-esteem	Self-esteem
27.	Behavioural confirmation	Behavioural confirmation
28.	Status	Status
29.	Comfort	Comfort
30.	Stimulation	Stimulation
31.	Physical wellbeing	Physical wellbeing; general health; health
32.	Mental wellbeing	Mental wellbeing
33.	Composure	Composure
34.	Positivity	Positivity
35.	Achievement	Achievement
36.	Conscientiousness	Conscientiousness
37.	Empathy	Empathy
38.	Initiative	Initiative

Note. Repeated words indicate how many times the term appeared in the wellbeing instruments.

Appendix 2.1 Twin studies of wellbeing of young people aged 12 – 25 years old.

	Category	Authors (Year)	Measure	Sample	Age	Sex	MZ pairs	DZ pairs	rMZ	rDZ	A/D (95% CI)	C (95% CI)	E (95% CI)
1.	Subjective	Van `t Ent et al. (2017)	Satisfaction With Life Scale; Subjective Happiness Scale	Netherlands Twin Registry	2 samples mean age = 18.1 and 17.2	M/F	62 pairs; 1 individual; 1 triplet MZ pair	46 pairs; 11 individuals; 60 siblings	.44[1]	.16	44		56
2.	Subjective	Bartels et al. (2012)	Satisfaction With Life Scale; Subjective Happiness Scale; Cantril's Ladder (in general)	Netherlands Twin Registry	15.7 (13.9 – 19.9)	M F OS	528 778	455 559 1085	.41 .47	.11 .24 .20	*No estimate provided*		
3.	Subjective	Bartels et al. (2013)	Satisfaction With Life Scale; Subjective Happiness Scale; Cantril Ladder (in general)	Netherlands Twin Registry	16.41 (12 – 20)	M F OS	551 792	476 571 1121	.33 .45	.20 .29 .20	34 (28, 39) 47 (42, 51)		66 (61, 72) 53 (39, 58)
4.	Subjective	Haworth et al. (2015)		Twins Early Development Study (UK)	16.32 (SD = .68)	M F OS							
			Brief Multidimensional Student Life Satisfaction Scale			M F OS	693 989	653 879 1480	.52 .60	.35 .39 .29	44 (36, 52)	11 (5, 18)	45 (42, 48)
			Subjective Happiness Scale			M F OS	691 990	656 877 1483	.43 .41	.19 .30 .16	34 (26, 40)	6 (2, 12)	60 (57, 64)

	Category	Authors (Year)	Measure	Sample	Age	Sex	MZ pairs	DZ pairs	rMZ	rDZ	A/D (95% CI)	C (95% CI)	E (95% CI)	
	Subjective	Haworth et al. (2016)	Subjective Happiness Scale; Brief Multidimensional Student Life Satisfaction Scale		Twins Early Development Study (UK)	16.55 (SD = .51)	M/F	167	208	.55[2]	.32	48 (20, 64)	7 (0, 30)	44 (36,
5.	Subjective (Quality of life)	Bartels & Boomsma (2009)		Netherlands Twin Registry	15.55 (SD = 1.50)	M F OS	321 449	264 326 503						
			Cantril's Ladder (in general)			M F OS			.42 .53	.10 .26 .16	A = 22 (6, 24) D = 25 (23, 25)		53 (52, 57)	
			Satisfaction With Life Scale			M F OS			.44 .48	.08 .22 .17	A = 9 (0, 13) D = 38 (17, 50)		53 (48, 58)	
			Cantril's Ladder (present)			M F OS			.40 .32	.09 .15 .21	A = 35 (22, 41) D = 1 (0, 1)		64 (64, 59)	
			Subjective Happiness Scale			M F OS			.31 .46	.08 .17 .15	A = 14 (13, 27) D = 26 (11, 32)		60 (59, 66)	
6.	Subjective (Quality of life in general)	Van der Aa et al. (2010)	Cantril Ladder	Netherlands Twin Registry	14, 18	M F OS	290 432	232 309 566	.38/.23[3] .46/.35	.20/.14 .36/.10 .24/.11	30 (18, 37) 43 (25, 52)	0 (0, 9) 3 (0, 18)	70 (63, 77) 54 (48, 60)	
7.	Happiness	Bartels et al. (2010)	Subjective Happiness Scale	Netherlands Twin Registry	12, 19	M F OS	433 616 families	370 448 386 families	.19 .42	.08 .17 .18	22 (16, 28) 41 (37, 45)		78 (72, 84) 59 (55, 63)	

	Category	Authors (Year)	Measure	Sample	Age	Sex	MZ pairs	DZ pairs	rMZ	rDZ	A/D (95% CI)	C (95% CI)	E (95% CI)
8.	Subjective and eudaimonic wellbeing	Krapohl et al. (2014)	17 measures including life satisfaction, happiness, hopefulness	Twins Early Development Study (UK)	16	M/F	704	1106	.54	.35	35 (22, 49)	17 (6, 28)	47 (43, 52)
9.	Subjective and eudaimonic wellbeing	Wootton et al. (2017)		Twins Early Development Study (UK)	16.32 (± 0.68)	M F OS	1142 1640 individuals	1058 1418 2370 individuals					
			Subjective Happiness Scale								41 (36, 44)	0 (0, 3)	59 (56, 62)
			Multidimensional student life satisfaction scale; brief multidimensional student life satisfaction scale								46 (38, 54)	10 (4, 16)	44 (42, 47)
			Subjective Health								33 (22, 38)	0 (0, 8)	67 (62, 72)
			Children's hope scale								35 (21, 40)	0 (0, 11)	65 (60, 70)
			Gratitude questionnaire								36 (22, 45)	4 (0, 15)	60 (55, 65)
			Curiosity and exploration inventory								39 (32, 44)	0 (0, 6)	61 (56, 66)
			Short grit scale								38 (33, 43)	0 (0, 10)	62 (57, 67)
			Ambition scale								41 (32, 45)	0 (0, 6)	59 (55, 65)
			Optimism (life orientation test – revised)								37 (32, 42)	0 (0, 9)	63 (58, 68)
			Relatedness (basic psychological needs satisfaction scale)								49 (45, 52)	0 (0, 4)	51 (48, 55)
			Autonomy (basic psychological needs satisfaction scale)								44 (35, 48)	0 (0, 7)	56 (52, 59)
			Competence (basic psychological needs satisfaction scale)								45 (39, 49)	0 (0, 4)	55 (51, 58)
			Meaningful life measure								46 (40, 50)	0 (0, 4)	54 (50, 57)
			Trust (single item on social trust)								54 (40, 62)	0 (0, 11)	46 (38, 54)
10.	Subjective and eudaimonic wellbeing	Wang et al. (2017)		Twins Early Development Study (UK)	17.85 (SD = 0.77)	M/F	354	779					

	Category	Authors (Year)	Measure	Sample	Age	Sex	MZ pairs	DZ pairs	rMZ	rDZ	A/D (95% CI)	C (95% CI)	E (95% CI)
			Positive affect (Positive affect scale)						.49	.19	47 (40, 54)		53 (46, 60)
			Negative affect (Negative affect scale)						.38	.15	35 (27, 42)		65 (58, 73)
			Subjective Happiness Scale						.47	.16	44 (36, 51)		56 (49, 64)
			Brief multidimensional student life satisfaction scale						.57	.34	60 (54, 65)		40 (35, 46)
			Gratitude questionnaire						.58	.22	55 (49, 61)		45 (39, 51)
			Meaningful life measure						.53	.23	52 (45, 58)		48 (42, 55)
			Autonomy (basic psychological needs satisfaction scale)						.52	.23	51 (44, 57)		49 (43, 56)
			Competence (basic psychological needs satisfaction scale)						.51	.23	50 (43, 56)		50 (44, 57)
			Relatedness (basic psychological needs satisfaction scale)						.57	.21	54 (47, 60)		46 (40, 53)
11.	Wellbeing and wider traits	Fagnani et al. (2017)		Italian Twin Registry	16.3	M/F	281 individuals	493 individuals					
			Optimism (life orientation test – revised)						.59	.19	55 (44, 65)		45 (35, 56)
			Self-esteem (Rosenberg scale)						.48	.21	45 (33, 55)		55 (45, 67)
			Self-derogation (Rosenberg scale)						.29	.14	29 (16, 41)		71 (59, 84)
			Subjective Happiness Scale						.44	.31	48 (36, 58)		52 (42, 64)

Note. Age measured in years; Sex: M = Male, F = Female, OS = twin pairs of opposite sex; rMZ = correlation between monozygotic twins; rDZ = correlation between dizygotic twins; A/D = heritability estimate based on additive genetic influence (A) and non-additive genetic influences (D); C = shared (or common) environmental influences; E = nonshared environmental influences. [1]Twin correlations and parameter estimates based on pooled samples of 724 individuals, with mean age 27 (±1.8), which controlled for age. [2]Estimates for baseline assessment before intervention. [3]Parents not divorced/divorced.

Appendix 3.1 Copy of the wellbeing scales in TEDS

3.1.1 Web measures

3.1.1.1 Life satisfaction: Multidimensional Student's Life Satisfaction Scale (Huebner, 1994)

Thinking about <u>the past few months</u>, please indicate how much you agree with the following statements.

	Strongly agree	⟵		⟶		**Strongly disagree**
I am fun to be around.	☐	☐	☐	☐	☐	☐
I have a bad time with my friends.	☐	☐	☐	☐	☐	☐
There are lots of things I can do well.	☐	☐	☐	☐	☐	☐
I learn a lot at school.	☐	☐	☐	☐	☐	☐
My family is better than most.	☐	☐	☐	☐	☐	☐
There are many things about school I don't like.	☐	☐	☐	☐	☐	☐
My friends will help me if I need it.	☐	☐	☐	☐	☐	☐
I like myself.	☐	☐	☐	☐	☐	☐
There are lots of fun things to do where I live.	☐	☐	☐	☐	☐	☐
My friends treat me well.	☐	☐	☐	☐	☐	☐
Most people like me.	☐	☐	☐	☐	☐	☐
I enjoy being at home with my family.	☐	☐	☐	☐	☐	☐
My family gets along well together.	☐	☐	☐	☐	☐	☐
My parents treat me fairly.	☐	☐	☐	☐	☐	☐
I like being in school.	☐	☐	☐	☐	☐	☐
I wish I had different friends.	☐	☐	☐	☐	☐	☐
I enjoy school activities.	☐	☐	☐	☐	☐	☐
I wish I lived in a different house.	☐	☐	☐	☐	☐	☐
I have enough friends.	☐	☐	☐	☐	☐	☐
I wish there were different people in my neighbourhood/area.	☐	☐	☐	☐	☐	☐
I like where I live.	☐	☐	☐	☐	☐	☐

3.1.1.2 Subjective happiness: Subjective Happiness Scale (Lyubomirsky & Lepper, 1999)

For each of the following statements and/or questions, *please select the point on the scale* that you feel is most appropriate in describing you.

1. In general, I consider myself:

1	2	3	4	5	6	7
Not a very happy person						A very happy person

2. Compared to most of my peers, I consider myself:

1	2	3	4	5	6	7
Less happy						More happy

3. Some people are generally very happy. They enjoy life regardless of what is going on, getting the most out of everything. To what extent does this describe you?

1	2	3	4	5	6	7
Not at all						A great deal

4. Some people are generally not very happy. Although they are not depressed, they never seem as happy as they might be. To what extent does this describe you?

1	2	3	4	5	6	7
Not at all						A great deal

3.1.1.3 Hopefulness: Children's Hope Scale (Snyder et al., 1997)

The sentences below describe how people think about themselves and how they do things in general. For each sentence, please think about how you are in most situations.
Select the box that describes you the best. There are no right or wrong answers.

	All of the time	←			→	**None of the time**
I think I am doing pretty well.	☐	☐	☐	☐	☐	☐
I can think of many ways to get the things in life that are most important to me.	☐	☐	☐	☐	☐	☐
I am doing just as well as others my age.	☐	☐	☐	☐	☐	☐
When I have a problem, I can come up with lots of ways to solve it.	☐	☐	☐	☐	☐	☐
I think the things I have done in the past will help me in the future.	☐	☐	☐	☐	☐	☐
Even when others want to quit, I know that I can find ways to solve the problem.	☐	☐	☐	☐	☐	☐

3.1.1.4 Gratitude: Gratitude Questionnaire-6 (McCullough, Emmons, & Tsang, 2002)

To what extent do you agree with the following statements?

	Strongly agree ⟵						⟶ **Strongly disagree**
I have so much in life to be thankful for.	☐	☐	☐	☐	☐	☐	☐
If I had to list everything I felt grateful for, it would be a very long list.	☐	☐	☐	☐	☐	☐	☐
When I look at the world, I don't see much to be grateful for.	☐	☐	☐	☐	☐	☐	☐
I am grateful to a wide variety of people.	☐	☐	☐	☐	☐	☐	☐
As I get older I find myself more able to appreciate the people, events, and situations that have been part of my life history.	☐	☐	☐	☐	☐	☐	☐
Long amounts of time can go by before I feel grateful to something or someone.	☐	☐	☐	☐	☐	☐	☐

3.1.1.5 Optimism: Life Orientation Test – Revised (Scheier, Carver, & Bridges, 1994)

To what extent do the following statements describe you?

	Very much like me ⟵				⟶ **Not like me at all**
In uncertain times, I usually expect the best.	☐	☐	☐	☐	☐
If something can go wrong for me, it will.	☐	☐	☐	☐	☐
I'm always optimistic about my future.	☐	☐	☐	☐	☐
I hardly ever expect things to go my way.	☐	☐	☐	☐	☐
I rarely count on good things happening to me.	☐	☐	☐	☐	☐
Overall, I expect more good things to happen to me than bad.	☐	☐	☐	☐	☐

3.1.1.6 Ambition: Ambition Scale (Duckworth, Peterson, Matthews, & Kelly, 2007)

To what extent do the following statements describe you?

	Very much like me	⟷			Not like me at all
I aim to be the best in the world at what I do.	☐	☐	☐	☐	☐
I am ambitious.	☐	☐	☐	☐	☐
Setbacks don't discourage me.	☐	☐	☐	☐	☐
I am a hard worker.	☐	☐	☐	☐	☐
I finish whatever I begin.	☐	☐	☐	☐	☐
Achieving something of lasting importance is the highest goal in life.	☐	☐	☐	☐	☐
I think achievement is overrated.	☐	☐	☐	☐	☐
I am driven to succeed.	☐	☐	☐	☐	☐
I am diligent.	☐	☐	☐	☐	☐

3.1.1.7 Curiosity: Curiosity And Exploration Inventory (Kashdan, Rose, & Fincham, 2004)

To what extent do you agree with the following statements?

	Strongly agree			⟷			**Strongly disagree**
I would describe myself as someone who actively seeks as much information as I can in a new situation.	☐	☐	☐	☐	☐	☐	☐
When I am participating in an activity, I tend to get so involved that I lose track of time.	☐	☐	☐	☐	☐	☐	☐
I frequently find myself looking for new opportunities to grow as a person (e.g., information, people, resources).	☐	☐	☐	☐	☐	☐	☐
I am *not* the type of person who probes deeply into new situations or things.	☐	☐	☐	☐	☐	☐	☐
When I am actively interested in something, it takes a great deal to interrupt me.	☐	☐	☐	☐	☐	☐	☐
My friends would describe me as someone who is "extremely intense" when in the middle of doing something.	☐	☐	☐	☐	☐	☐	☐
Everywhere I go, I am looking out for new things or experiences.	☐	☐	☐	☐	☐	☐	☐

3.1.1.8 Grit: Short Grit Scale (Duckworth & Quinn, 2009)

To what extent do the following statements describe you?

	Very much like me me at all		⟷		Not like
New ideas and projects sometimes distract me from previous ones.	☐	☐	☐	☐	☐
I have been obsessed with a certain idea or project for a short time but later lost interest.	☐	☐	☐	☐	☐
I often set a goal but later choose to pursue a different one.	☐	☐	☐	☐	☐
I have difficulty maintaining my focus on projects that take more than a few months to complete.	☐	☐	☐	☐	☐

3.1.1.9 Health:Single Item From KIDSCREEN-52 (Ravens-Sieberer et al., 2008)

	Excellent	**Very good**	**Good**	**Fair**	**Poor**
In general, how would you say your health is?	☐	☐	☐	☐	☐

3.1.2 Booklet measures

3.1.2.1 Life satisfaction: Brief Multidimensional Student Life Satisfaction Scale (Seligson, Huebner, & Valois, 2003)

These six questions ask about how satisfied you generally feel with different areas of your life. Please tick the answer that best represents how you feel about each area.

	Very dissatisfied	Quite dissatisfied	Slightly dissatisfied	Neutral	Slightly satisfied	Quite satisfied	Very satisfied
1. How do you generally feel about your family life?	☐	☐	☐	☐	☐	☐	☐
2. How happy are you with your friendships?	☐	☐	☐	☐	☐	☐	☐
3. How do you feel about your school experience?	☐	☐	☐	☐	☐	☐	☐
4. How do you feel about yourself?	☐	☐	☐	☐	☐	☐	☐
5. How do you feel about where you live?	☐	☐	☐	☐	☐	☐	☐
6. How do you feel about your life, overall?	☐	☐	☐	☐	☐	☐	☐

3.1.2.2 Subjective happiness: Subjective Happiness Scale (Lyubomirsky & Lepper, 1999)

For each of the following statements and/or questions, please select the point on the scale that you feel is most appropriate in describing you

1. In general, I consider myself:

1: A very unhappy person	2	3	4: Neutral	5	6	7: A very happy person
☐	☐	☐	☐	☐	☐	☐

2. Compared to people of my age, I consider myself:

1: Much less happy	2	3	4: Average	5	6	7: Much more happy
☐	☐	☐	☐	☐	☐	☐

3. Some people are generally very happy and enjoy life regardless of what is going on. To what extent does this describe you?

1: Not at all	2	3	4: Mixed	5	6	7: A great deal
☐	☐	☐	☐	☐	☐	☐

4. Some people are generally not very happy. Whatever is going on, they never seem as happy as they might be. To what extent does this describe you?

1: Not at all	2	3	4: Mixed	5	6	7: A great deal
☐	☐	☐	☐	☐	☐	☐

3.1.2.3 Relatedness: Basic Psychological Needs Satisfaction Scale (Deci & Ryan, 2000)

To what extent do the following statements describe you?

	1: Not at all true	2	3	4: Somewhat true	5	6	7: Very true
I really like the people I interact with	☐	☐	☐	☐	☐	☐	☐
I get along with people I come into contact with	☐	☐	☐	☐	☐	☐	☐
I pretty much keep to myself and don't have a lot of social contacts	☐	☐	☐	☐	☐	☐	☐
I consider the people I regularly interact with to be my friends	☐	☐	☐	☐	☐	☐	☐
People in my life care about me	☐	☐	☐	☐	☐	☐	☐
There are not many people that I am close to	☐	☐	☐	☐	☐	☐	☐
The people I interact with regularly do not seem to like me much	☐	☐	☐	☐	☐	☐	☐
People are generally pretty friendly towards me	☐	☐	☐	☐	☐	☐	☐

3.1.2.4 Autonomy: Basic Psychological Needs Satisfaction Scale (Deci & Ryan, 2000

To what extent do the following statements describe you?

	1: Not at all true	2	3	4: Somewhat true	5	6	7: Very true
I feel like I am free to decide for myself how to live my life	☐	☐	☐	☐	☐	☐	☐
I feel pressured in my life	☐	☐	☐	☐	☐	☐	☐
I generally feel free to express my ideas and opinions	☐	☐	☐	☐	☐	☐	☐
In my daily life, I frequently have to do what I am told	☐	☐	☐	☐	☐	☐	☐
People I interact with on a daily basis tend to take my feelings into consideration	☐	☐	☐	☐	☐	☐	☐
I feel like I can pretty much be myself in my daily situations	☐	☐	☐	☐	☐	☐	☐
There is not much opportunity for me to decide for myself how to do things in my daily life	☐	☐	☐	☐	☐	☐	☐

3.1.2.5 Competence: Basic Psychological Needs Satisfaction Scale (Deci & Ryan, 2000

To what extent do the following statements describe you?

	1: Not at all true	2	3	4: Somewhat true	5	6	7: Very true
Often, I do not feel very competent	☐	☐	☐	☐	☐	☐	☐
People I know tell me I am good at what I do	☐	☐	☐	☐	☐	☐	☐
I have been able to learn interesting new skills recently	☐	☐	☐	☐	☐	☐	☐
Most days I feel a sense of accomplishment from what I do	☐	☐	☐	☐	☐	☐	☐
In my life I do not get much of a chance to show how capable I am	☐	☐	☐	☐	☐	☐	☐
I often do not feel very capable	☐	☐	☐	☐	☐	☐	☐

3.1.2.6 Meaning in life: Meaningful Life Measure (Morgan & Farsides, 2009)

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree
1. My life interests and excites me	☐	☐	☐	☐	☐	☐	☐
2. I find it satisfying to think about what I have accomplished in life	☐	☐	☐	☐	☐	☐	☐
3. I have a philosophy of life that really gives my living significance	☐	☐	☐	☐	☐	☐	☐
4. I have a clear idea of what my future goals and aims are	☐	☐	☐	☐	☐	☐	☐
5. My life is significant	☐	☐	☐	☐	☐	☐	☐

3.1.2.7 Trust: Social Trust ('Gallup World Poll', 2006)

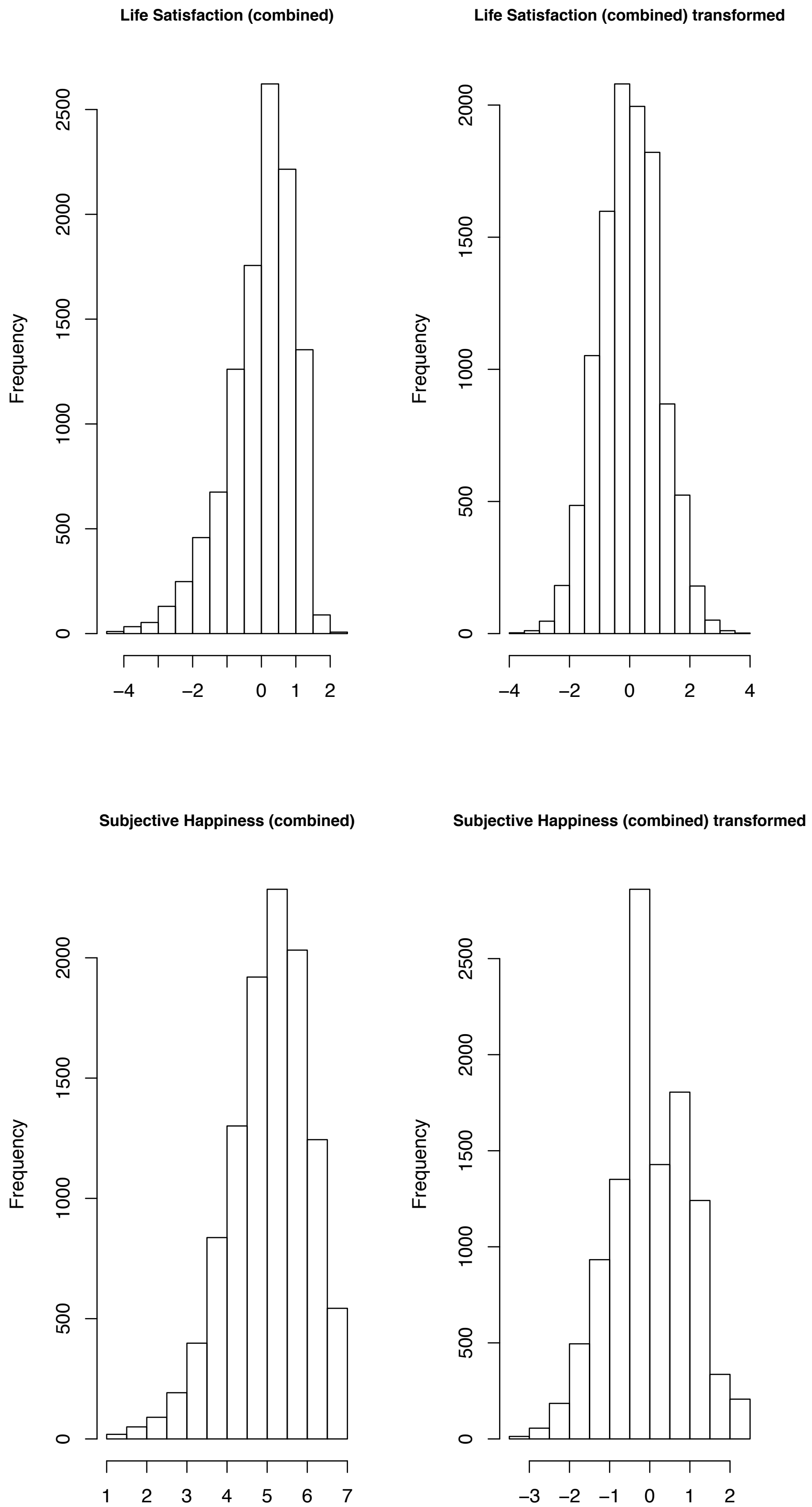
	Yes	No
1. In general I think people can be trusted	☐	☐

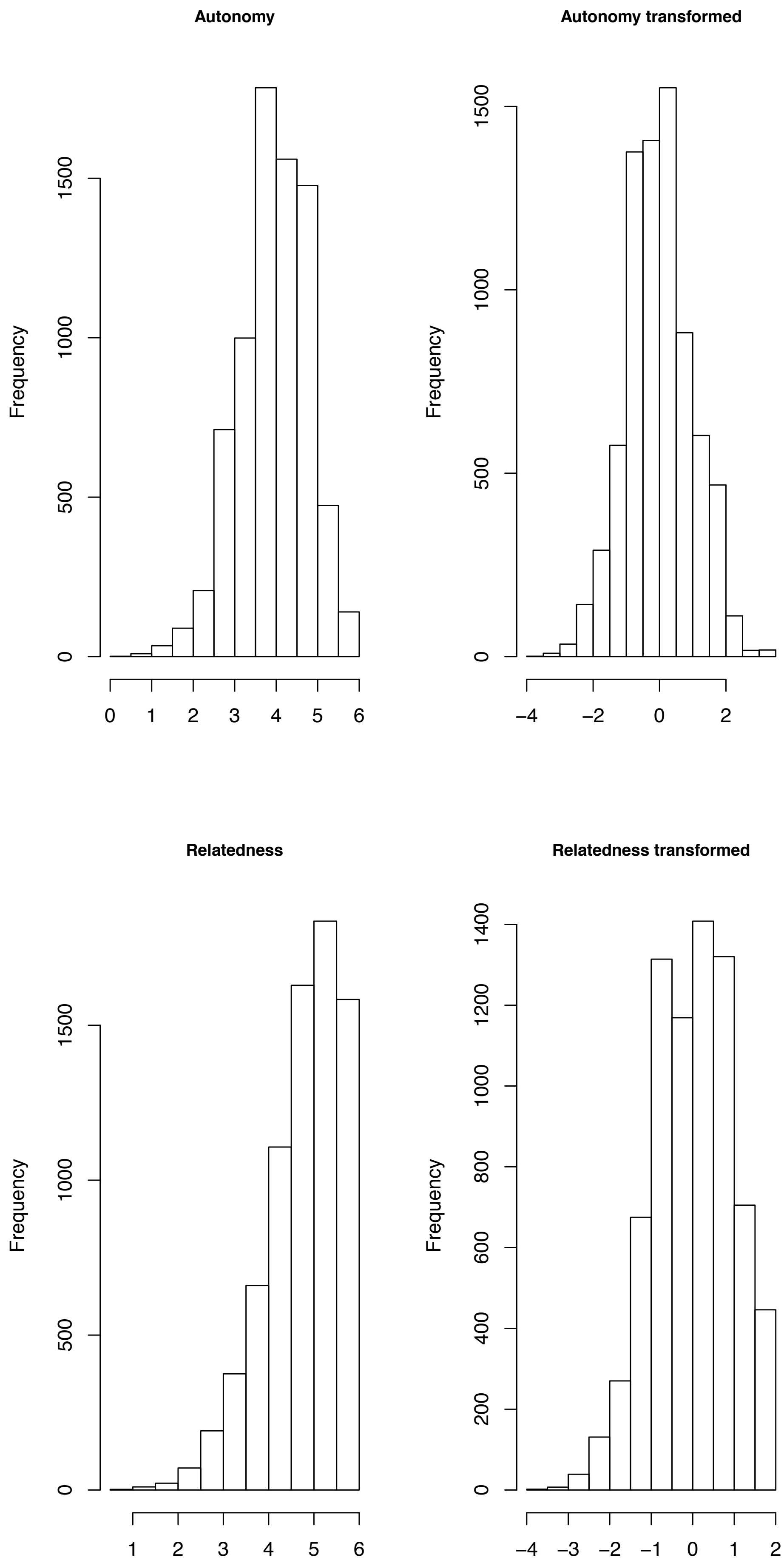
3.1.2.8 Mindfulness: Mindful Attention Awareness Scale (Van Dam, Earleywine, & Borders, 2010)

The following questions are interested in what you are most usually like. For each of the following statements please select the option that best describes how often you feel that way.

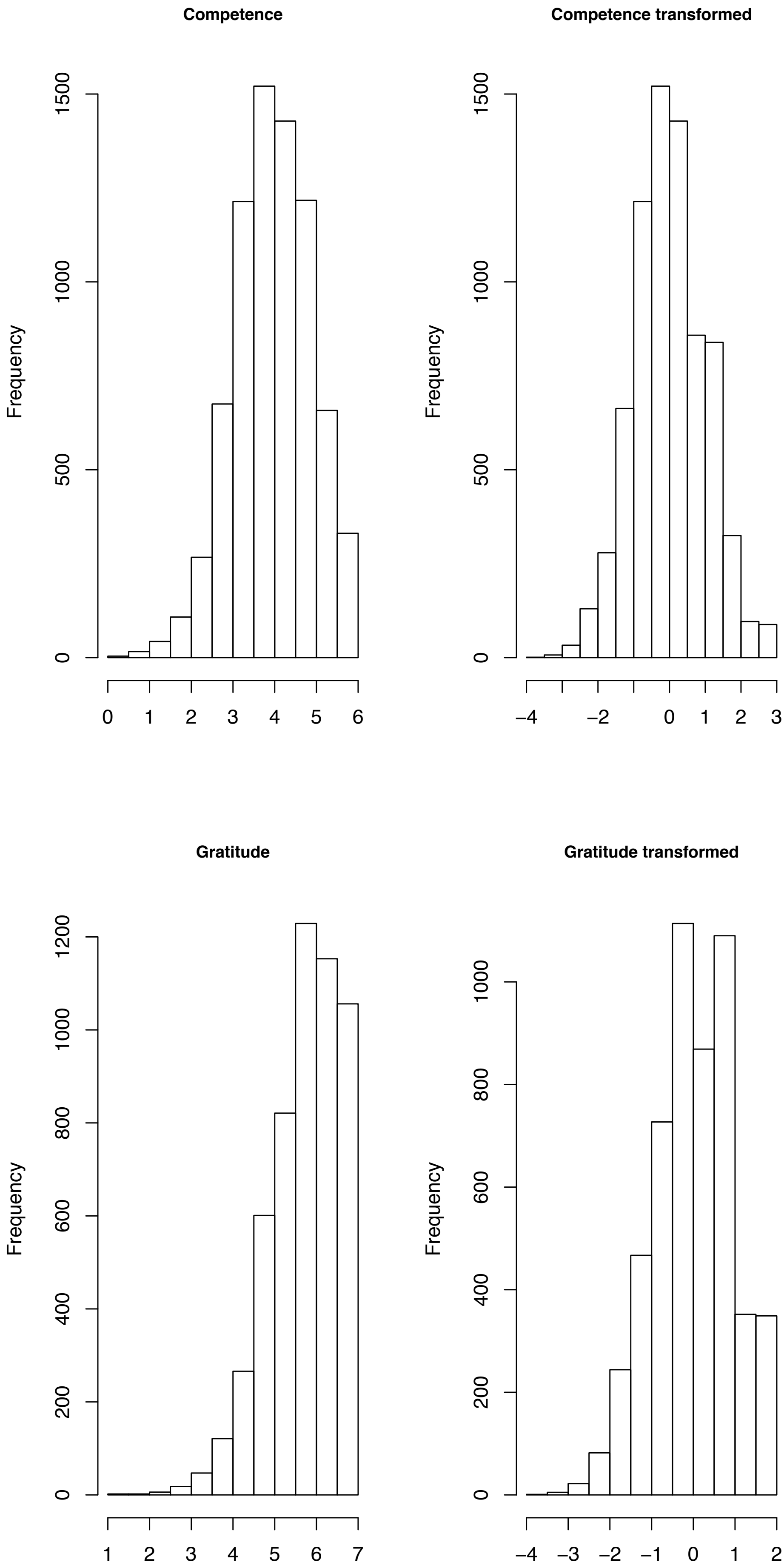
	Almost Never	Not Very Often at All	Not Very Often	Somewhat Often	Very Often	Almost Always
1. It seems that I am doing things automatically without really being aware of what I am doing	☐	☐	☐	☐	☐	☐
2. I rush through activities without being really attentive to them.	☐	☐	☐	☐	☐	☐
3. I focus so much on a future goal I want to achieve that I don't pay attention to what I am doing right now to reach it	☐	☐	☐	☐	☐	☐
4. I do jobs, chores, or schoolwork automatically without being aware of what I'm doing	☐	☐	☐	☐	☐	☐
5. I find myself doing things without paying attention	☐	☐	☐	☐	☐	☐

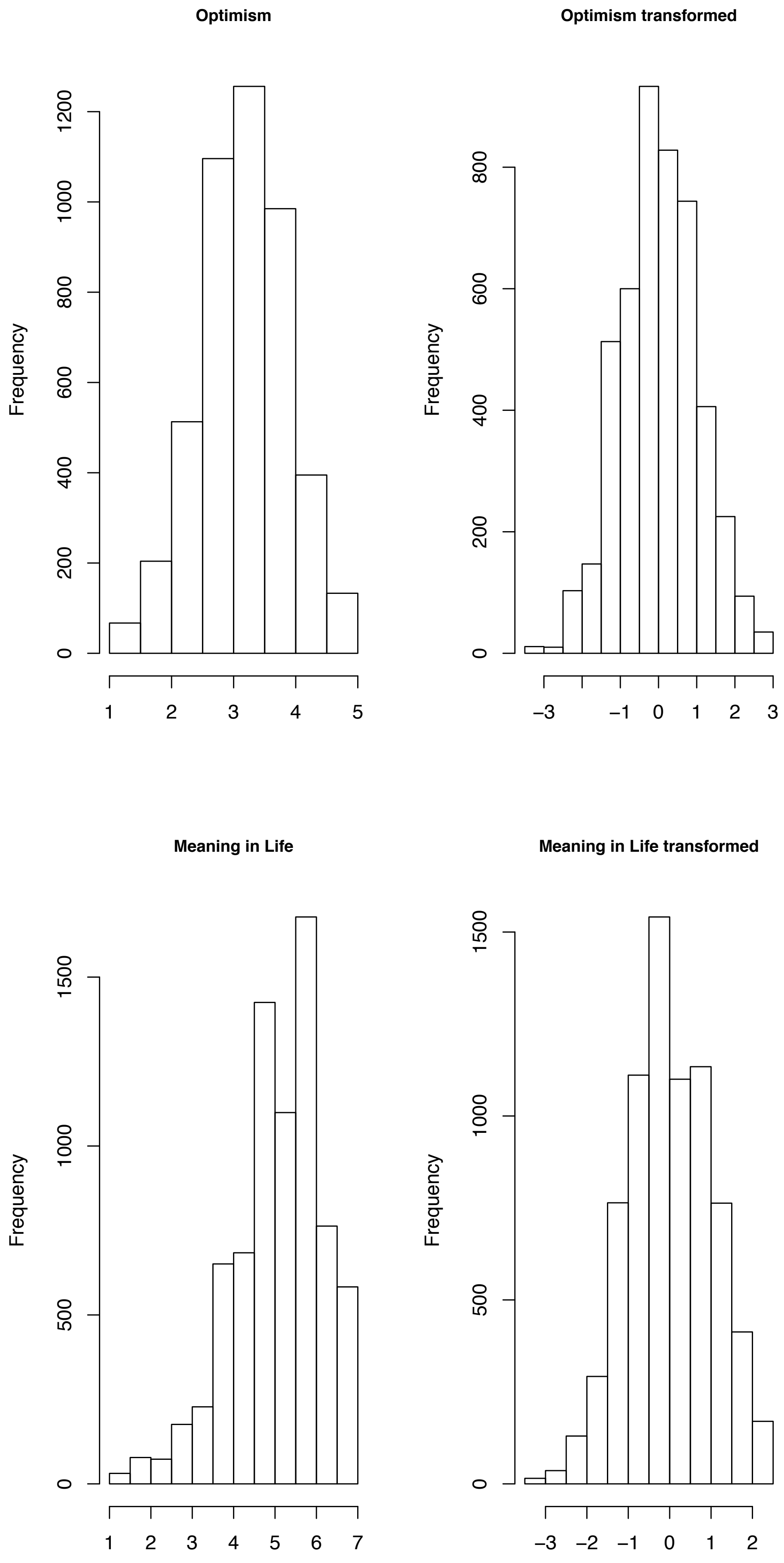
Appendix 3.2 Histograms of untransformed and van der Waerden transformed wellbeing measures.

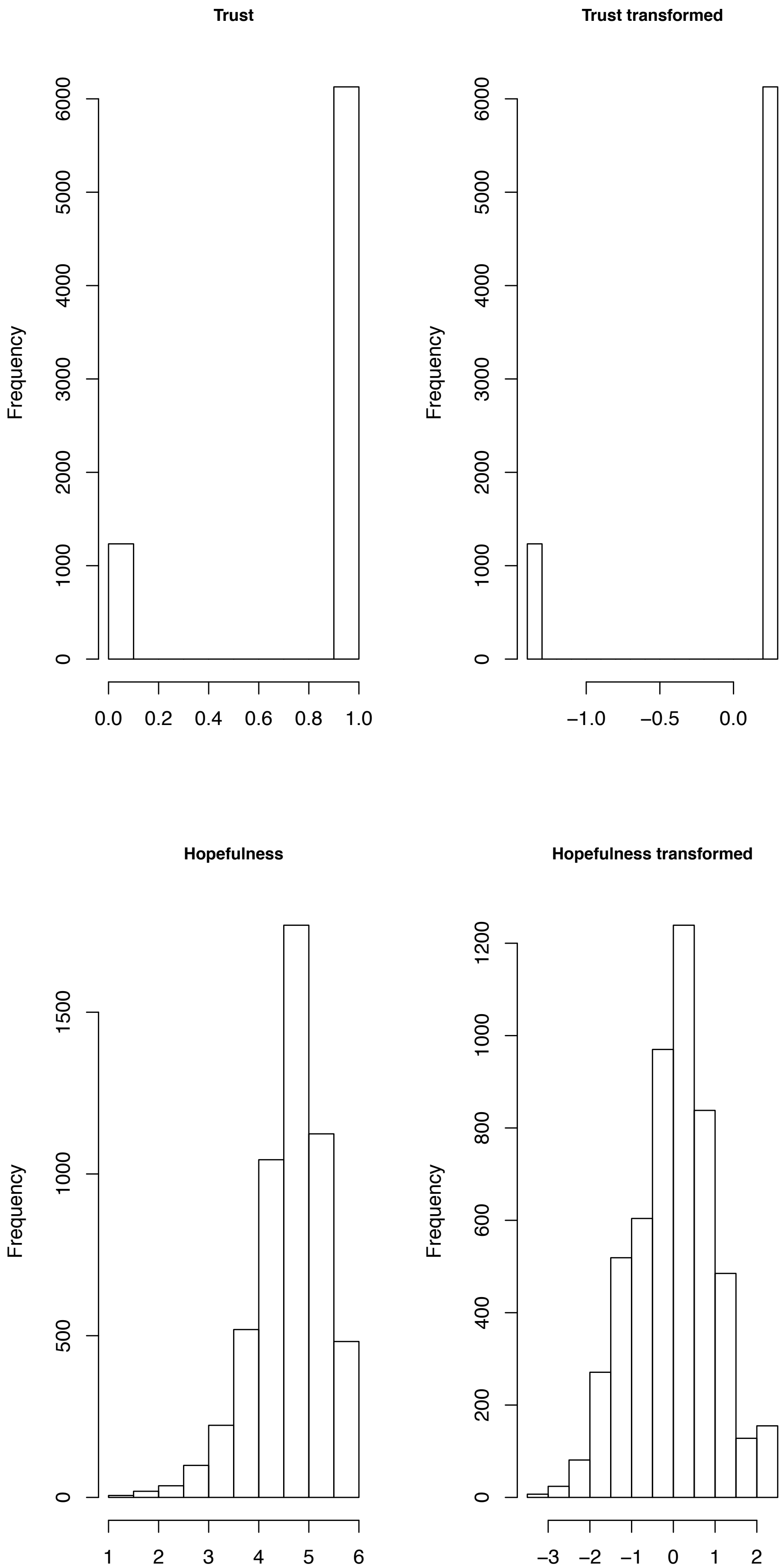


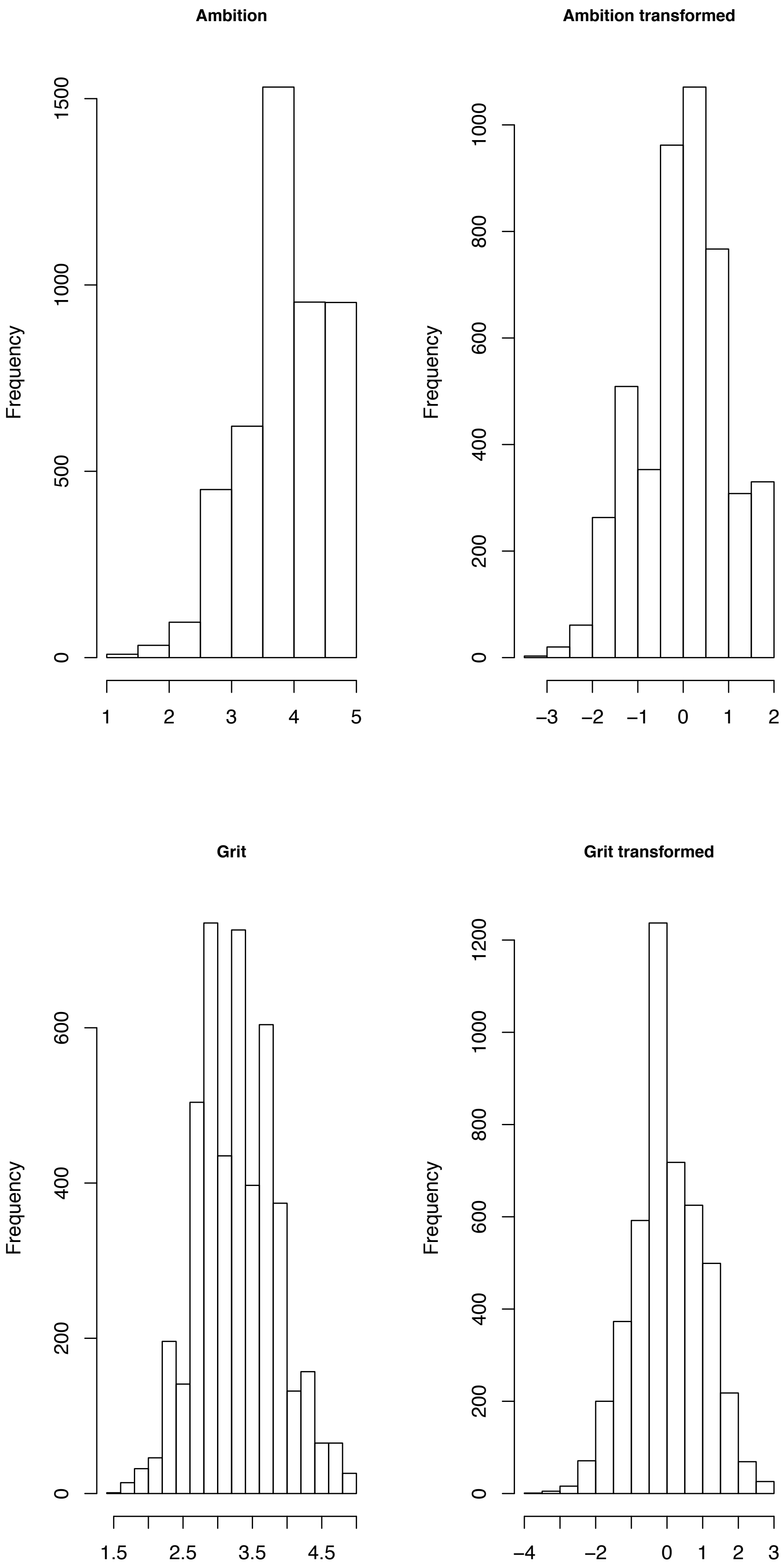


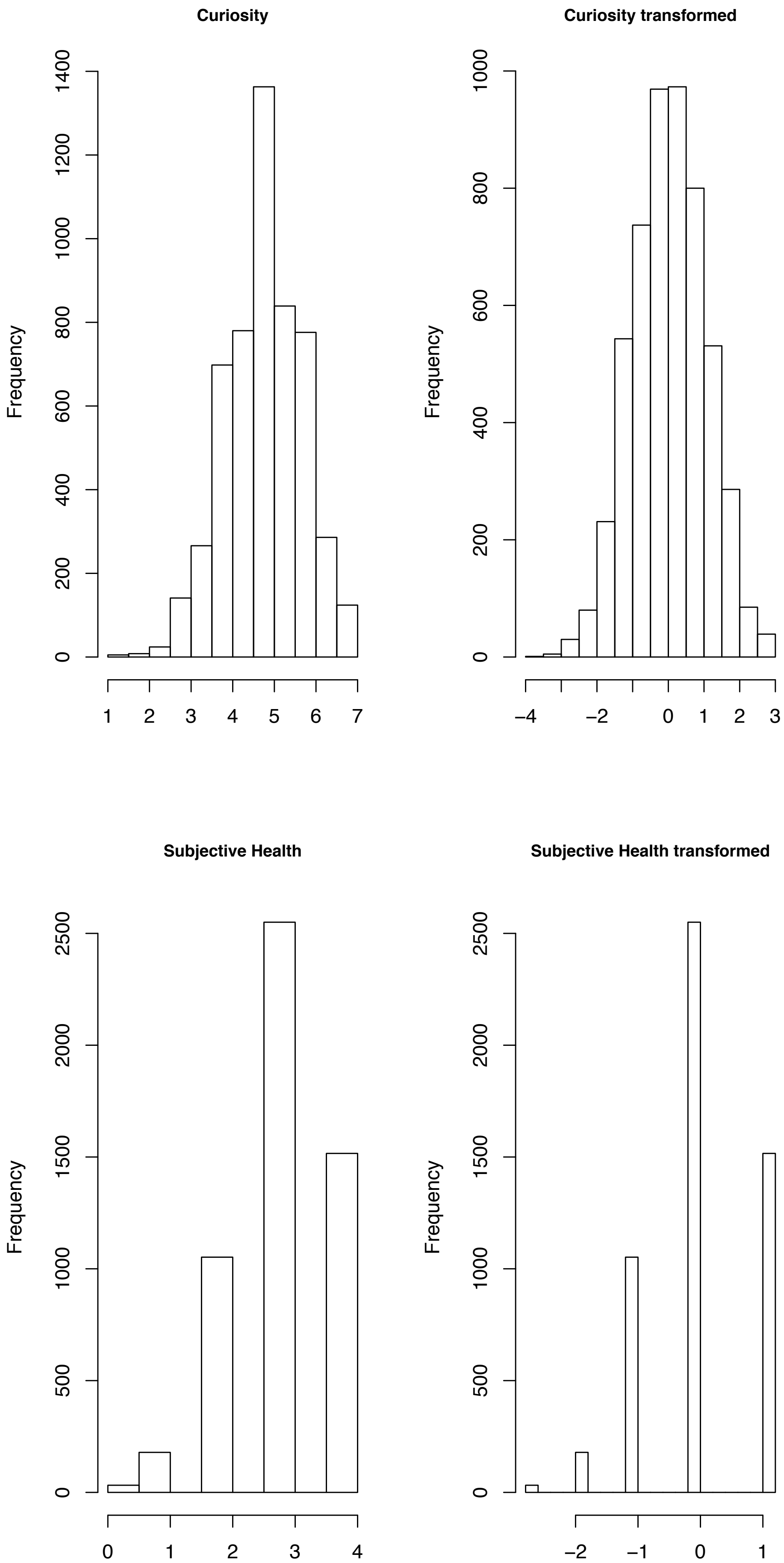
Autonomy
Frequency
0
500
1000
1500
0 1 2 3 4 5 6
Autonomy transformed
Frequency
0
500
1000
1500
−4 −2 0 2
Relatedness
Frequency
0
500
1000
1500
1 2 3 4 5 6
Relatedness transformed
Frequency
0
200
400
600
800
1000
1200
1400
−4 −3 −2 −1 0 1 2


Competence
Competence transformed
Gratitude
Gratitude transformed
Frequency
0
500
1000
1500
0 1 2 3 4 5 6
−4 −2 0 1 2 3
200
400
600
800
1000
1200
1 2 3 4 5 6 7
−4 −3 −2 −1 0 1 2


Optimism
Frequency
0
200
400
600
800
1000
1200
1
2
3
4
5
Optimism transformed
Frequency
0
200
400
600
800
−3
−1
0
1
2
3
Meaning in Life
Frequency
0
500
1000
1500
1
2
3
4
5
6
7
Meaning in Life transformed
Frequency
0
500
1000
1500
−3
−2
−1
0
1
2


Trust
Trust transformed
Hopefulness
Hopefulness transformed
Frequency
0
1000
2000
3000
4000
5000
6000
0.0
0.2
0.4
0.6
0.8
1.0
−1.0
−0.5
0.0
500
1500
1
2
3
4
5
6
200
400
600
800
1200
−3
−2
−1


Ambition
Ambition transformed
Grit
Grit transformed
Frequency
Frequency
Frequency
Frequency
0
500
1000
1500
1
2
3
4
5
0
200
400
600
800
1000
−3
−2
−1
0
1
2
0
200
400
600
1.5
2.5
3.5
4.5
0
200
400
600
800
1000
1200
−4
−2
0
1
2
3


Curiosity
Frequency
Curiosity transformed
Frequency
Subjective Health
Frequency
Subjective Health transformed
Frequency

Appendix 3.3 Twin modelling: variance-covariance matrix construction; saturated models and equating variance

Twin modelling uses statistical processes to compare the predictions of a model based on theory with the given observational data to estimate components of variance (Neale & Cardon, 2013). To calculate the correlation between twin pairs, each twin is first randomly selected as 'Twin 1' or 'Twin 2', which creates two samples of data for both MZ twins and DZ twins. For example (not real data):

MZ twin pairs			DZ twin pairs		
Family ID	Twin 1	Twin 2	Family ID	Twin 1	Twin 2
1	5	4	*6*	4	5
2	4	5	*7*	6	5
3	6	7	*8*	5	7
4	4	3	*9*	3	4
5	7	6	*10*	7	6

The formula to calculate correlation requires the calculation of variance and covariance. The variance measures the spread of the data around the mean. The formula to calculate the mean is:

$$\mu = \frac{\Sigma x}{n}$$

where the mean (μ) is the sum of the individuals scores (x) divided by the number of individuals (n). The formula to calculate variance is:

$$V = \sigma_x^2 = \frac{\sum(x_i - \mu)^2}{n - 1}$$

where the deviation of each individual from the mean is calculated by subtracting the mean score (μ) from the i-th individual's score (x_i). This deviation is squared, and summed for all individuals, then divided by the number of individuals (n) minus 1. For example, the mean and variance for Twin 1 MZ twins from the example data above is:

$$\mu = \frac{(5+4+6+4+7)}{5} = 5.2$$

$$V_1 = \sigma_1^2 = \frac{\sum((5-5.2)^2 + (4-5.2)^2 + (6-5.2)^2 + (4-5.2)^2 + (7-5.2)^2)}{5-1}$$

$$\sigma_1^2 = \frac{6.8}{4} = 1.7$$

Covariance measures the association between two variables, and represents the degree to which the dispersion around the mean of one variable is related to the dispersion around the mean of another variable. In twin modelling, we calculate the covariance between twin pairs, to estimate the degree to which the scores for twins allocated as 'Twin 1' are related to the scores for twins allocated as 'Twin 2'. We do this separately for MZ and DZ twins because we expect a higher covariance between MZ twins based on the knowledge that MZ twins are more genetically similar than DZ twins. The formula to calculate covariance is:

$$Cov_{xy} = \sigma_{xy}^2 = \frac{\sum(x_i - \mu_x)(y_i - \mu_y)}{N-1}$$

where the sum of the deviation from the mean for each individual allocated as Twin 1 ($x_i - \mu_x$) is multiplied by the co-twin's deviation from the mean ($y_i - \mu_y$) and divided by the number of twin pairs minus 1. For example, the covariance for MZ twin pairs is:

$$Cov_{(1,2)} = \sigma_{(1,2)}^2$$

$$= \frac{(5-5.2)(4-5) + (4-5.2)(5-5) + (6-5.2)(7-5) + (4-5.2)(3-5) + (7-5.2)(6-5)}{5-1}$$

$$Cov_{(1,2)} = \sigma_{(1,2)}^2 = \frac{6}{4} = 1.5$$

Correlation is then calculated using the formula:

$$r_{xy} = \frac{Cov_{xy}}{\sqrt{\sigma_x^2 \sigma_y^2}}$$

where the covariance between twins allocated as Twin 1 (x) and twins allocated as Twin 2 (y) is divided by the square root of the product of the variance for Twin 1 and Twin 2. For example, given the variance in MZ twins allocated as 'Twin 1' is 1.7, the variance for 'Twin 2' twins is 2.5 (proof not shown), and the covariance is 1.5, the correlation between MZ twins is:

$$r_{(1,2)} = \frac{1.5}{\sqrt{1.7 \times 2.5}} = 0.73$$

Because the correlation is the covariance divided by the dispersion within each twin order, correlation is the standardised covariance. Correlation is often preferred to covariance because it does not rely on the scale of a measure, and is comparable across different measures and scales. In twin modelling, we use matrices to hold the variance and covariance for MZ and DZ twins, and then use matrix multiplication to calculate the correlation. The variance-covariance matrices for MZ and DZ twins are:

$$\text{MZ} = \begin{array}{c c} & \begin{array}{cc} \text{Twin 1} & \text{Twin 2} \end{array} \\ \begin{array}{c} \text{Twin 1} \\ \text{Twin 2} \end{array} & \begin{bmatrix} V_1 & Cov_{(1,2)} \\ Cov_{(1,2)} & V_2 \end{bmatrix} \end{array}$$

$$\text{DZ} = \begin{array}{c c} & \begin{array}{cc} \text{Twin 1} & \text{Twin 2} \end{array} \\ \begin{array}{c} \text{Twin 1} \\ \text{Twin 2} \end{array} & \begin{bmatrix} V_1 & Cov_{(1,2)} \\ Cov_{(1,2)} & V_2 \end{bmatrix} \end{array}$$

Six statistics are held in the matrices, which are the variance for Twin 1 (V_1), Twin 2 (V_2) and the covariance between Twin 1 and Twin 2 ($Cov_{(1,2)}$), for both MZ and DZ twins. Both matrices are symmetrical, because the covariance between Twin 1 and Twin 2 (upper right element) is identical to covariance between Twin 2 and Twin 1 (lower left element). Adding additional variables is simple using matrices, which will be discussed in the next section, 'extensions to the basic twin model'.

All the twin modelling in this thesis has been performed on the OpenMx package (Neale et al., 2015) in R (R Core Team, 2016). Though the variance and covariance can be calculated by hand, if a twin pair's data were incomplete and one twin had data but their co-twin's data was missing, then we would not be able to use this data. Using structural equation modelling (SEM) with full-information maximum likelihood estimation (FIML) allows us to incorporate the data of one twin from an incomplete twin pair. It is computationally more efficient to use OpenMx. The variance-covariance matrix can be standardised, resulting in a correlation matrix, using the formula:

solve(sqrt(I*V))%&%V

where V is the variance-covariance matrix, and I is an identity matrix, which is a square matrix with 1s on the principal diagonal and 0s for all other elements. The annotation * represents element multiplication. The matrix multiplication annotation %&% represents calculation of the quadratic product, which means pre- and post- multiplication of the matrices. For example, for matrix A and matrix B, A%&%B represents A%*%B%*%A, where %*% simply represents matrix multiplication of row by column.

Multiplying by an identity matrix will leave the matrix unchanged when using standard multiplication. In this case, multiplying the variance-covariance matrix (V) by the identity matrix (I) extracts the variances:

$$\mathrm{I} * \mathrm{V} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} * \begin{bmatrix} V_1 & Cov_{(1,2)} \\ Cov_{(1,2)} & V_2 \end{bmatrix} = \begin{bmatrix} V_1 & 0 \\ 0 & V_2 \end{bmatrix}$$

sqrt() simply takes the square root of each element:

$$\mathrm{sqrt}(\mathrm{I} * \mathrm{V}) = \begin{bmatrix} \sqrt{V_1} & 0 \\ 0 & \sqrt{V_2} \end{bmatrix}$$

solve()inverts the matrix:

$$solve = \begin{bmatrix} \sqrt{V_1} & 0 \\ 0 & \sqrt{V_2} \end{bmatrix}^{-1} = \begin{bmatrix} \frac{1}{\sqrt{V_1}} & 0 \\ 0 & \frac{1}{\sqrt{V_2}} \end{bmatrix}$$

then %&%V pre- and post-multiplies matrix V by the matrix we have calculated to hold the inverted square root of the variance:

$$\mathrm{solve}(\mathrm{sqrt}(\mathrm{I} * \mathrm{V}))\%\&\%\mathrm{V} =$$

$$\begin{bmatrix} \frac{1}{\sqrt{V_1}} & 0 \\ 0 & \frac{1}{\sqrt{V_2}} \end{bmatrix} \% * \% \begin{bmatrix} V_1 & Cov_{(1,2)} \\ Cov_{(1,2)} & V_2 \end{bmatrix} \% * \% \begin{bmatrix} \frac{1}{\sqrt{V_1}} & 0 \\ 0 & \frac{1}{\sqrt{V_2}} \end{bmatrix}$$

The first rule of matrix multiplication is that the number of columns in the first matrix must match the number of rows in the second. The product of these two matrices will have the number of rows from the first matrix (in this case, 2) and the number of columns in the second matrix (2). The elements in the resulting matrix are calculated by the cross-product of the corresponding row in the first matrix and the corresponding column in the second matrix. For example:

$$\begin{bmatrix} \frac{1}{\sqrt{V_1}} & 0 \\ 0 & \frac{1}{\sqrt{V_2}} \end{bmatrix} \% * \% \begin{bmatrix} V_1 & Cov_{(1,2)} \\ Cov_{(1,2)} & V_2 \end{bmatrix}$$

$$= \begin{bmatrix} \frac{1}{\sqrt{V_1}} \times V_1 + 0 \times Cov_{(1,2)} & \frac{1}{\sqrt{V_1}} \times Cov_{(1,2)} + 0 \times V_2 \\ 0 \times V_1 + \frac{1}{\sqrt{V_2}} \times Cov_{(1,2)} & 0 \times Cov_{(1,2)} + \frac{1}{\sqrt{V_2}} \times V_2 \end{bmatrix}$$

$$= \begin{bmatrix} \frac{V_1}{\sqrt{V_1}} & \frac{Cov_{(1,2)}}{\sqrt{V_1}} \\ \frac{Cov_{(1,2)}}{\sqrt{V_2}} & \frac{V_2}{\sqrt{V_2}} \end{bmatrix}$$

which is then multiplied again by the matrix of the inverted square root of the variance:

$$\begin{bmatrix} \frac{V_1}{\sqrt{V_1}} & \frac{Cov_{(1,2)}}{\sqrt{V_1}} \\ \frac{Cov_{(1,2)}}{\sqrt{V_2}} & \frac{V_2}{\sqrt{V_2}} \end{bmatrix} \% * \% \begin{bmatrix} \frac{1}{\sqrt{V_1}} & 0 \\ 0 & \frac{1}{\sqrt{V_2}} \end{bmatrix}$$

$$= \begin{bmatrix} \frac{V_1}{\sqrt{V_1}} \times \frac{1}{\sqrt{V_1}} + \frac{Cov_{(1,2)}}{\sqrt{V_1}} \times 0 & \frac{V_1}{\sqrt{V_1}} \times 0 + \frac{Cov_{(1,2)}}{\sqrt{V_1}} \times \frac{1}{\sqrt{V_2}} \\ \frac{Cov_{(1,2)}}{\sqrt{V_2}} \times \frac{1}{\sqrt{V_1}} + \frac{V_2}{\sqrt{V_2}} \times 0 & \frac{Cov_{(1,2)}}{\sqrt{V_2}} \times 0 + \frac{V_2}{\sqrt{V_2}} \times \frac{1}{\sqrt{V_2}} \end{bmatrix}$$

$$= \begin{bmatrix} 1 & \frac{Cov_{(1,2)}}{\sqrt{V_1 V_2}} \\ \frac{Cov_{(1,2)}}{\sqrt{V_2 V_1}} & 1 \end{bmatrix} = \begin{bmatrix} 1 & r_{1,2} \\ r_{1,2} & 1 \end{bmatrix}$$

When this formula is applied to the MZ example data given above, where the Twin 1 variance was 1.7, Twin 2 variance was 2.5 and covariance was 1.5, we get:

$$\begin{bmatrix} \frac{1}{\sqrt{V_1}} & 0 \\ 0 & \frac{1}{\sqrt{V_2}} \end{bmatrix} \%*\% \begin{bmatrix} V_1 & Cov_{(1,2)} \\ Cov_{(1,2)} & V_2 \end{bmatrix} \%*\% \begin{bmatrix} \frac{1}{\sqrt{V_1}} & 0 \\ 0 & \frac{1}{\sqrt{V_2}} \end{bmatrix}$$

$$= \begin{bmatrix} \frac{1}{\sqrt{1.7}} & 0 \\ 0 & \frac{1}{\sqrt{2.5}} \end{bmatrix} \%*\% \begin{bmatrix} 1.7 & 1.5 \\ 1.5 & 2.5 \end{bmatrix} \%*\% \begin{bmatrix} \frac{1}{\sqrt{1.7}} & 0 \\ 0 & \frac{1}{\sqrt{2.5}} \end{bmatrix}$$

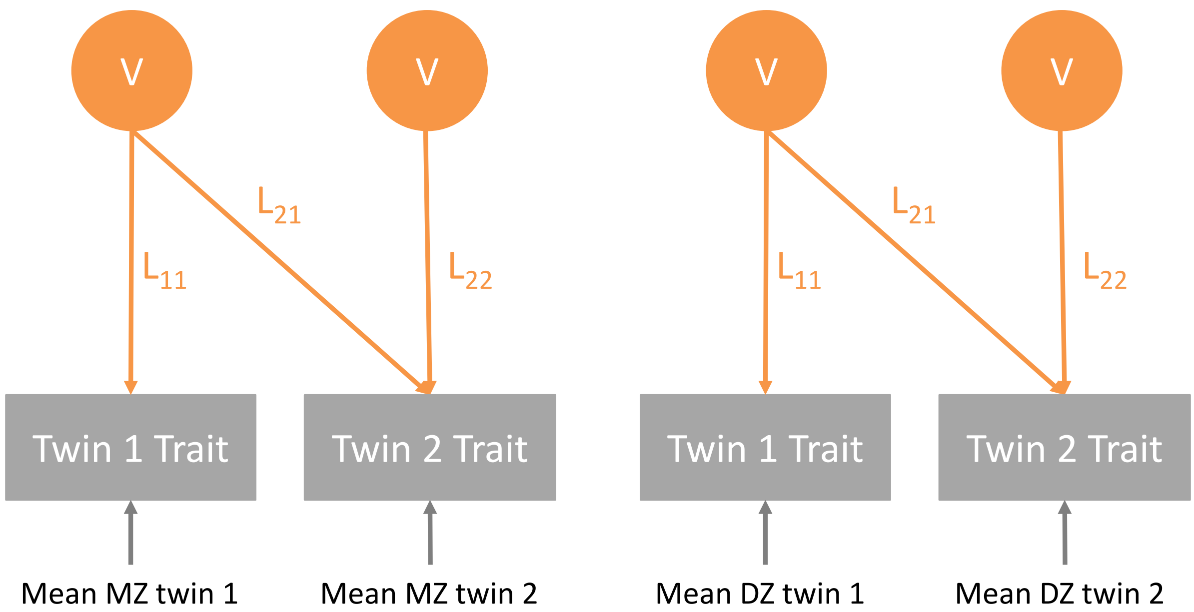
$$= \begin{bmatrix} \frac{1.7}{\sqrt{1.7}} & \frac{1.5}{\sqrt{1.7}} \\ \frac{1.5}{\sqrt{2.5}} & \frac{2.5}{\sqrt{2.5}} \end{bmatrix} \%*\% \begin{bmatrix} \frac{1}{\sqrt{1.7}} & 0 \\ 0 & \frac{1}{\sqrt{2.5}} \end{bmatrix} = \begin{bmatrix} 1 & \frac{1.5}{\sqrt{1.7 \times 2.5}} \\ \frac{1.5}{\sqrt{2.5 \times 1.7}} & 1 \end{bmatrix}$$

$$= \begin{bmatrix} 1 & 0.73 \\ 0.73 & 1 \end{bmatrix} = \begin{bmatrix} 1 & r_{1,2} \\ r_{1,2} & 1 \end{bmatrix}$$

The correlation between the twin pairs is therefore 0.73. These basic formulas are applied in twin modelling using Cholesky and Gaussian specifications.

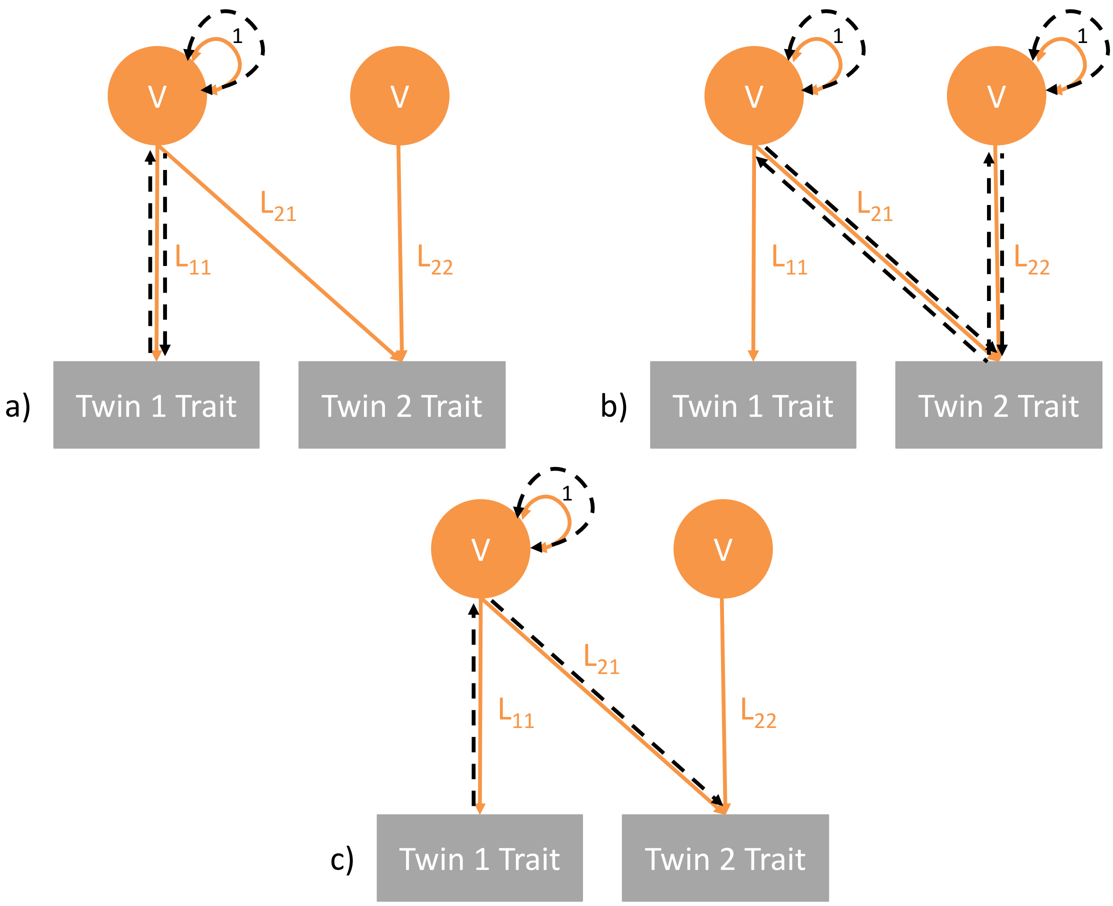
3.3.1 Path tracing: saturated Cholesky model

Path analysis was developed by geneticist Sewall Wright in 1918, which incorporates our knowledge of relatedness between participants with observed correlations (Wright, 1921). Using path analysis, we can visually represent the relationship between the observed variables in diagrams and derive estimates of the latent parameters within the model. It is mathematically identical to matrix multiplication, though instead of estimating the variance (σ^2), we fix the variance to 1 and estimate path coefficients (Plomin, DeFries, Knopik, & Neiderheiser, 2013). Appendix Figure 3.1 is a path diagram of the variance for a given trait using the Cholesky specification. In SEM modelling, observed variables are displayed in squares, latent variables are displayed in circles, causal paths are indicated by single-headed arrows, and double-headed arrows represent covariance paths. We model MZ and DZ twins separately, because we expect the covariance between MZ twins to be higher than DZ twins. The Cholesky specification models the variance for twins allocated as ‘Twin 1’, decomposes how much of the variance for Twin 1 is shared with Twin 2, and then estimates the remaining (unique) variance for Twin 2.



Appendix Figure 3.3.1 Path diagram of the parameters estimated in the saturated Cholesky model, for MZ and DZ twins. ‘Twin 1’ refers to the sample of twins randomly allocated as ‘Twin 1’, and ‘Twin 2’ refers to the sample of twins randomly allocated as ‘Twin 2’. V represents the variance. Circles represent latent factors. Grey boxes represent observed variables. Single-headed arrows show a causal path. The means are added for illustrative purposes. We estimate six path coefficients and four means, totalling 10 parameters. By path tracing, the variance in Twin 1 is $\boldsymbol{L_{11}^2}$, the variance in Twin 2 is $\boldsymbol{L_{21}^2} + \boldsymbol{L_{22}^2}$, and the covariance is $\boldsymbol{L_{11}} \times \boldsymbol{L_{21}}$. This is modelled separately for MZ and DZ twins. These estimates are identical to the matrix solution for the Cholesky covariance formula L%*%t(L).

The expected variance for a trait can be calculated by following Wright’s rules of path tracing (Wright, 1921). First, trace backwards, then forwards from variable to variable but never forward then back. This includes the variance for each latent variable to itself, which is not represented on Appendix Figure 3.1, but is a double-headed arrow from the latent variable to itself (see Appendix Figure 3.2). Second, you cannot pass through the same variable twice. Third, there is a maximum of one double-headed arrow per chain. This means that the double-headed arrow from the latent variable to itself is included, unless the chain includes another covariance path (this rule applies to the Gaussian model). Path tracing for the Cholesky univariate model is visualised in Appendix Figure 3.2. We can see that the legitimate path to Twin 1 is L_{11}^2, the legitimate path to Twin 2 is $L_{21}^2 + L_{22}^2$, and the legitimate covariance path from Twin 1 to Twin 2 is $L_{11}L_{21}$.



Appendix Figure 3.3.2 Visualisation of path tracing to estimate the variance and covariance of the saturated univariate model with Cholesky specification. The variance and covariance can be traced following the legitimate paths, which are highlighted by the black dashed lines. a) The variance in Twin 1 is calculated by $\boldsymbol{L_{11}} \times \mathbf{1} \times \boldsymbol{L_{11}} = \boldsymbol{L_{11}^2}$. b) The variance in Twin 2 is calculated by $\boldsymbol{L_{21}} \times \mathbf{1} \times \boldsymbol{L_{21}} + \boldsymbol{L_{22}} \times \mathbf{1} \times \boldsymbol{L_{22}} = \boldsymbol{L_{21}^2} + \boldsymbol{L_{22}^2}$. c) The covariance between Twin 1 and Twin 2 is $\boldsymbol{L_{11}} \times \mathbf{1} \times \boldsymbol{L_{21}} = \boldsymbol{L_{11}L_{21}}$.

3.3.2 The saturated univariate twin model: Cholesky specification

Using the Cholesky model, covariance between twins is estimated by L%*%t(L), where L is a lower triangular matrix:

$$\begin{array}{r c} & \begin{array}{cc} \text{V Twin 1} & \text{V Twin 2} \end{array} \\ \begin{array}{r} \text{Twin 1 trait} \\ \text{Twin 2 trait} \end{array} & \begin{bmatrix} L_{11} & 0 \\ L_{21} & L_{22} \end{bmatrix} \end{array}$$

This is a lower matrix because the variance for Twin 2 is not modelled to contribute to the variance in Twin 1 (see Appendix Figure 3.1). Matrix L is transposed by the function t(), which converts the rows and columns to columns and rows. Solving the equation for covariance in the Cholesky model using matrix multiplication gives:

$$Cov = \mathrm{L\% * \%t(L)} = \begin{bmatrix} L_{11} & 0 \\ L_{21} & L_{22} \end{bmatrix} * \begin{bmatrix} L_{11} & L_{21} \\ 0 & L_{22} \end{bmatrix}$$

$$= \begin{bmatrix} L_{11}L_{11} + 0 \times 0 & L_{11} \times L_{21} + 0 \times L_{22} \\ L_{21} \times L_{11} + L_{22} \times 0 & L_{21} \times L_{21} + L_{22} \times L_{22} \end{bmatrix} = \begin{bmatrix} L_{11}^2 & L_{11} \times L_{21} \\ L_{21} \times L_{11} & L_{21}^2 + L_{22}^2 \end{bmatrix}$$

This is identical to the solution from the path tracing above. The Cholesky model then uses this resulting variance-covariance matrix in the formula described above (solve(sqrt(I*L))%&%L), where the variance for each twin is on the principal diagonal, and the other elements hold the covariance between the twins.

Using the saturated Cholesky model, we are estimating a total of 10 parameters. We estimate the means for the sample of twins allocated as 'Twin 1' and twins allocated as 'Twin 2'. We also estimate the variance for Twin 1 (L_{11}), the variance for Twin 2 (L_{22}) and the variance for Twin 2 explained by the variance in Twin 1 (L_{21}). These five parameters are modelled separately for MZ and DZ twins, resulting in 10 estimated parameters, as shown in Appendix Figure 3.1. Using path tracing, the estimated variance and covariance is identical to the matrix solution.

3.3.3 The saturated univariate twin model: Gaussian specification

Alternatively, model fitting can use a Gaussian specification, which is mathematically equivalent to the Cholesky specification. The Gaussian model is often preferred because the order of the data is arbitrary. The Cholesky specification provides the covariance between Twin 1 and Twin 2 as the product of the variance in Twin 1 and the variance in Twin 1 that is shared with Twin 2 ($L_{11}L_{21}$). This will be different to the covariance if Twin 2 was entered into the model first, which is the product of the variance in Twin 2 and the variance in Twin 2 that is shared with Twin 1 ($L_{22}L_{21}$). However, allocation of twins within a pair to either 'Twin 1' or 'Twin 2' is random, therefore the order is arbitrary. In a Gaussian specification, the correlation between the variance is modelled, and consequently the order of the data in the model is irrelevant.

The saturated Gaussian model calculates covariance by S%*%R%*%t(S), where R is a symmetrical matrix of the correlations (r), with elements of 1 across the principal diagonal, and S is a diagonal matrix (square matrix with 0 in all elements except the principal diagonal) with standard deviations (SD) across the principal diagonal:

$$\begin{array}{ccc} & \text{V Twin 1} & \text{V Twin 2} \\ \text{R = V Twin 1} & \left[\begin{array}{c} 1 \\ r_{(2,1)} \end{array}\right. & \left.\begin{array}{c} r_{(1,2)} \\ 1 \end{array}\right] \\ \text{V Twin 2} & & \end{array}$$

$$\begin{array}{ccc} & \text{V Twin 1} & \text{V Twin 2} \\ \text{S = Twin 1 trait} & \left[\begin{array}{c} SD_1 \\ 0 \end{array}\right. & \left.\begin{array}{c} 0 \\ SD_2 \end{array}\right] \\ \text{Twin 2 trait} & & \end{array}$$

We can solve the covariance equation for the saturated Gaussian model:

$$Cov = \text{S\% * \%R\% * \%t(S)} = \begin{bmatrix} SD_1 & 0 \\ 0 & SD_2 \end{bmatrix} * \begin{bmatrix} 1 & r \\ r & 1 \end{bmatrix} * \begin{bmatrix} SD_1 & 0 \\ 0 & SD_2 \end{bmatrix}$$

$$= \begin{bmatrix} SD_1 \times 1 + 0 \times r & SD_1 \times r + 0 \times 1 \\ 0 \times 1 + SD_2 \times r & 0 \times r + SD_2 \times 1 \end{bmatrix} * \begin{bmatrix} SD_1 & 0 \\ 0 & SD_2 \end{bmatrix}$$

$$= \begin{bmatrix} SD_1 & SD_1 r \\ SD_2 r & SD_2 \end{bmatrix} * \begin{bmatrix} SD_1 & 0 \\ 0 & SD_2 \end{bmatrix} = \begin{bmatrix} SD_1^2 & SD_1 r SD_2 \\ SD_2 r SD_1 & SD_2^2 \end{bmatrix}$$

As the squared standard deviation (SD) is the variance, we can see that the elements on the principal diagonal are the variance for Twin 1 and Twin 2. The other elements give the covariance between the twins allocated as 'Twin 1', and twins allocated as 'Twin 2'. This is proven by rearranging the formula for correlation:

$$r_{xy} = \frac{Cov_{xy}}{\sqrt{\sigma_x^2 \sigma_y^2}}$$

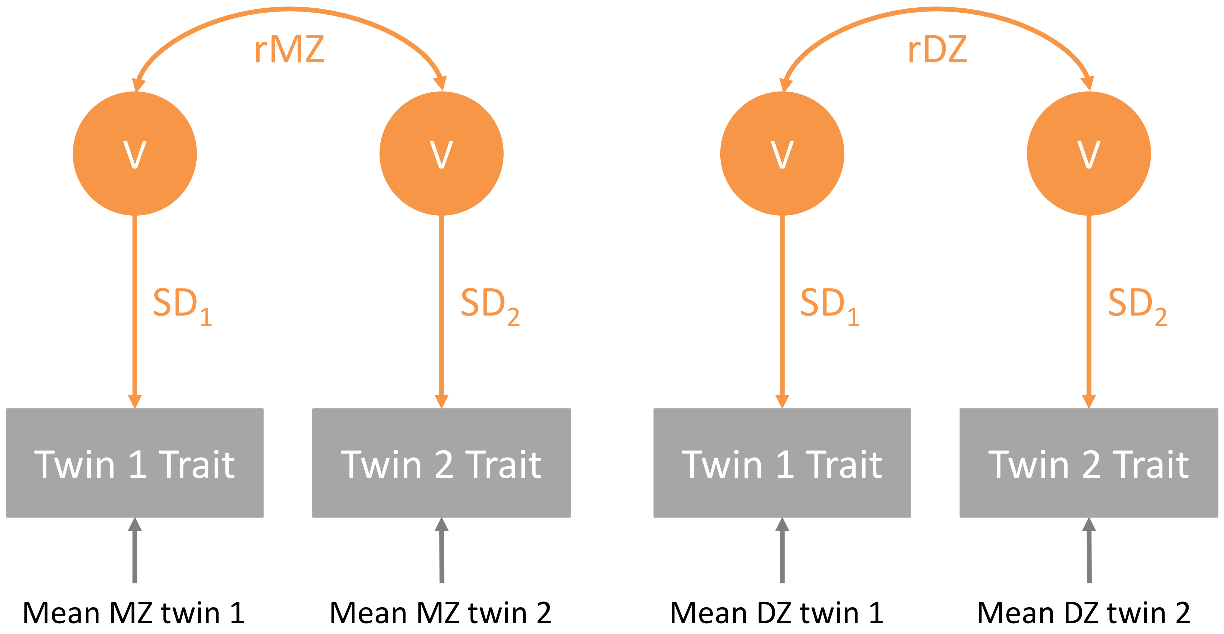
$$r_{(1,2)} = \frac{Cov_{(1,2)}}{\sqrt{SD_1^2 SD_2^2}}$$

$$r_{(1,2)} = \frac{Cov_{(1,2)}}{SD_1 SD_2}$$

$$SD_1 SD_2 r_{(1,2)} = Cov_{(1,2)}$$

The matrix multiplication for the saturated Gaussian model can be verified using path tracing, as shown in Appendix Figure 3.3. The variance for Twin 1 is SD_1^2, the variance for

Twin 2 is SD_2^2, and the covariance is $SD_1 r SD_2$. The Gaussian model also estimates 10 parameters, with four means (for Twin 1 and Twin 2, MZ and DZ pairs), standard deviations (for Twin 1 and Twin 2, MZ and DZ pairs), and two correlations (for MZ and DZ twins).



Appendix Figure 3.3.3 Path diagram of the parameters estimated in the saturated Gaussian model, for MZ and DZ twins. 'Twin 1' refers to the sample of twins from each twin pair randomly allocated as 'Twin 1', and 'Twin 2' refers to the sample of twins from each twin pair randomly allocated as 'Twin 2'. V represents the variance. The variance for the latent variable is 1, and not usually drawn onto path diagrams (see 3.2 for illustrative example). Circles represent latent factors. Grey boxes represent observed variables. Single-headed arrows show a causal path. Double-headed arrows represent covariance between two variables. By path tracing, the variance for Twin 1 is $\boldsymbol{SD_1 \times 1 \times SD_1 = SD_1^2}$, where 1 is the variance for the latent variable (V). The variance for Twin 2 is $\boldsymbol{SD_2 \times 1 \times SD_2 = SD_2^2}$. The covariance between Twin 1 and Twin 2 is $\boldsymbol{SD_1 \times rMZ \times SD_2}$ for MZ twins and $\boldsymbol{SD_1 \times rDZ \times SD_2}$ for DZ twins. MZ and DZ twins are modelled separately because we expect a higher correlation between MZ twins than DZ twins.

3.3.4 *Equating across twin order and zygosity: saturated univariate twin model*

The allocation of twins to either 'Twin 1' or 'Twin 2' is random, therefore, we would not expect the mean and variance for Twin 1 and Twin 2 to differ significantly. We would also expect the means and variances to be similar across zygosity, with no significant difference between MZ twins and DZ twins. Consequently, we equate the means and variances across twin order and zygosity, and test whether the model that has equal means and variances fits significantly worse than the fully saturated model. We can model this in both the Cholesky and Gaussian specification by creating submodels of the original model. This is easily performed in OpenMx by relabelling the different means with the same name. For example, to equate the means for MZ twins in a submodel with Cholesky specification, we would use the following code:

```
Sub1Model <- omxSetParameters(Sub1Model, labels=c("Mmz1","Mmz2"),
                free = T, values = 5, newlabels="Mmz1")
```

where the means for MZ Twin 1 (Mmz1) and MZ Twin 2 (Mmz2) are both relabelled as Mmz1 to provide one mean across all MZ twins, regardless of twin order.

After we have equated the means and variances across twin order and then across zygosity, we compare the submodels to the fully saturated model. The submodels will never have a better fit than the fully saturated model, because we are constraining the means and variances to be equal, which is not modelling the data exactly. However, if the submodels do not fit significantly worse than the fully saturated model, we can accept that the means and variances are equal across twin order and zygosity. This is achieved in OpenMx by using the code:

```
mxCompare(SatFit, Sub1Fit), mxCompare(SatFit, Sub2Fit)
```

which outputs the goodness of fit tests, comparing the fit of the model with equal means and variances across twin order (Sub1Fit) to the fit of the saturated model (SatFit), and the fit of equal means and variances across twin order and zygosity (Sub2Fit) to the saturated model (SatFit). The goodness of fit tests includes Akaike's Information Criteria (AIC), the minus 2*log-likelihoods (-2LL), and chi-square (χ^2). We expect a *p*-value greater than 0.05 for the likelihood ratio test based on the difference in log-likelihoods between the model and the submodel and the difference in the degrees of freedom. This means the model does not fit significantly worse when the means and variances are equated across twin order and zygosity.

3.3.5 Interpreting intraclass correlation

When we equate the means and variances across twin order, we are essentially converting the correlation into an intraclass correlation. This accounts for the random allocation of a twin in a twin pair to 'Twin 1' or 'Twin 2'. The standard formulas for calculating the mean, variance, covariance and correlation, shown at the start of section appendix 3.1.1 are manipulated to equate the means and variances (Fisher, 1925). The overall mean is calculated by:

$$Omean = M = \frac{\Sigma(x_1 + x_2)}{2N}$$

where the overall mean (M) is the sum of the individuals allocated as Twin 1 (x_1) and the individuals allocated as Twin 2 (x_2) divided by twice the total number of twin pairs (N). The formula for the variance is:

$$V = \sigma_o^2 = \frac{\sum(x_{i1} - M)^2 + \sum(x_{i2} - M)^2}{2N - 1}$$

where the deviation is calculated separately for each twin in a pair. The overall mean (M) is subtracted from the Twin 1 score from the i-th twin pair (x_{i1}) and squared, and the overall mean (M) is subtracted from the Twin 2 score from the i-th twin pair (x_{i2}) and squared. These deviations are summed for both twins, added across twin order, and divided by twice the total number of twin pairs (N) minus 1. For example, the overall mean and variance for MZ twins using the previous example data would be:

$$M = \frac{(5+4+6+4+7)+(4+5+7+3+6)}{2\times 5} = 5.1$$

$$\sigma_o^2 = \frac{\sum((5-5.1)^2+(4-5.1)^2+(6-5.1)^2+(4-5.1)^2+(7-5.1)^2)}{2\times 5-1} + \frac{\sum((4-5.1)^2+(5-5.1)^2+(7-5.1)^2+(3-5.1)^2+(6-5.1)^2)}{2\times 5-1}$$

$$\sigma_o^2 = \frac{6.85+10.5}{9} = 1.88$$

The covariance is similar to the original formula, but uses the overall mean instead of separate means for Twin 1 and Twin 2:

$$Cov_{(1,2)} = \sigma^2_{(1,2)} = \frac{\sum(x_1 - M)(x_2 - M)}{N-1}$$

Using this formula, the covariance between the MZ twins is:

$$Cov_{(1,2)} = \sigma^2_{(1,2)} = \frac{(5-5.1)(4-5.1)+(4-5.1)(5-5.1)+(6-5.1)(7-5.1)+(4-5.1)(3-5.1)+(7-5.1)(6-5.1)}{5-1}$$

$$Cov_{(1,2)} = \frac{5.95}{4} = 1.49$$

The correlation is the covariance standardised by dividing by the overall variance:

$$r_{(1,2)} = \frac{Cov_{(1,2)}}{\sigma_o^2}$$

By applying this formula to the above example MZ data, the intraclass correlation between the MZ twins is calculated by:

$$r_{(1,2)} = \frac{1.49}{1.88} = 0.79$$

An intraclass correlation is interpreted similarly to a correlation, ranging between -1 and 1. A positive intraclass correlation close to 1 indicates high similarity within twin pairs compared to the similarity between twin pairs. A low intraclass correlation indicates there is little similarity between twins within the same twin pair. A negative correlation suggests that the variation within the twin pairs is greater than the variation between twin pairs. Because we expect the similarity within twin pairs to be greater than the similarity between twin pairs, we expect positive intraclass correlations.

3.3.6 Controlling for age and sex: saturated univariate twin model

In twin modelling, it is standard practice to include age and sex as covariates. We use linear regression to estimate the predicted mean of a trait after controlling for age and sex:

$$y_m = M + \beta_a A + \beta_s S$$

where y_m is the expected mean, M is the observed mean, β_a is the slope increase in the expected mean for each unit change in age (A), holding the effects of sex (S) constant, and β_s is the slope increase in the expected mean for each unit change in sex (S), holding the effects of age (A) constant. In OpenMx, we specify the expected mean as the observed mean plus the effects of age and sex:

```
(Omean + bCov%*%Cov1, Omean + bCov%*%Cov2)
```

where Omean is the observed mean, bCov is a 2 by 1 matrix holding the beta coefficients for age and sex, Cov1 is a 2 by 1 matrix of the age and sex of Twin 1, and Cov2 is a 2 by 1 matrix of the age and sex of Twin 2. The OpenMx formula is applied by:

$$Omean + bCov\% * \%Cov1, Omean + bCov\% * \%Cov2$$

$$M + \begin{bmatrix} \beta_A \\ \beta_S \end{bmatrix} * \begin{bmatrix} A_1 \\ S_1 \end{bmatrix} = M + \beta_A A_1 + \beta_S S_1$$

$$M + \begin{bmatrix} \beta_A \\ \beta_S \end{bmatrix} * \begin{bmatrix} A_2 \\ S_2 \end{bmatrix} = M + \beta_A A_2 + \beta_S S_2$$

As shown, OpenMx evaluates the overall mean across all data, equating across twin order and zygosity. We apply the model across twin order and zygosity (shown with one beta estimate for age, β_A, and one beta estimate for sex, β_S), but we enter the individual data for Twin 1 and Twin 2 within a twin pair separately. This accounts for differences in when twins responded to data collection, which is not necessarily the same time as their co-twin. It also accounts for sex differences in DZ twins. Notably, accounting for age and sex like this assumes that there is no difference in the means and variances across twin order and zygosity.

Appendix 3.4 Worked example to calculate the phenotypic correlation and A, C and E estimates for the bivariate model

For example, to calculate the phenotypic correlation (rPH) between two traits:

$$solve\big(sqrt(I*V)\big) = \sqrt{\begin{bmatrix}1 & 0\\0 & 1\end{bmatrix} * \begin{bmatrix}a_{11}^2 + c_{11}^2 + e_{11}^2 & a_{21}a_{22} + c_{21}c_{22} + e_{21}e_{22}\\a_{21}a_{22} + c_{21}c_{22} + e_{21}e_{22} & a_{21}^2a_{22}^2 + c_{21}^2c_{22}^2 + e_{21}^2e_{22}^2\end{bmatrix}}^{-1}$$

$$= \begin{bmatrix}\frac{1}{\sqrt{a_{11}^2 + c_{11}^2 + e_{11}^2}} & 0\\0 & \frac{1}{\sqrt{a_{21}^2a_{22}^2 + c_{21}^2c_{22}^2 + e_{21}^2e_{22}^2}}\end{bmatrix}$$

$$rPH = solve\big(sqrt(I*V)\big)\% * \%V\% * \%solve\big(sqrt(I*V)\big)$$

rPH

$$= \begin{bmatrix}\frac{1}{\sqrt{a_{11}^2 + c_{11}^2 + e_{11}^2}} & 0\\0 & \frac{1}{\sqrt{a_{21}^2a_{22}^2 + c_{21}^2c_{22}^2 + e_{21}^2e_{22}^2}}\end{bmatrix}$$

$$* \begin{bmatrix}a_{11}^2 + c_{11}^2 + e_{11}^2 & a_{21}a_{22} + c_{21}c_{22} + e_{21}e_{22}\\a_{21}a_{22} + c_{21}c_{22} + e_{21}e_{22} & a_{21}^2a_{22}^2 + c_{21}^2c_{22}^2 + e_{21}^2e_{22}^2\end{bmatrix}$$

$$* \begin{bmatrix}\frac{1}{\sqrt{a_{11}^2 + c_{11}^2 + e_{11}^2}} & 0\\0 & \frac{1}{\sqrt{a_{21}^2a_{22}^2 + c_{21}^2c_{22}^2 + e_{21}^2e_{22}^2}}\end{bmatrix}$$

$$= \begin{bmatrix}1 & \frac{a_{21}a_{22} + c_{21}c_{22} + e_{21}e_{22}}{\sqrt{a_{11}^2 + c_{11}^2 + e_{11}^2} \times \sqrt{a_{21}^2a_{22}^2 + c_{21}^2c_{22}^2 + e_{21}^2e_{22}^2}}\\\frac{a_{21}a_{22} + c_{21}c_{22} + e_{21}e_{22}}{\sqrt{a_{11}^2 + c_{11}^2 + e_{11}^2} \times \sqrt{a_{21}^2a_{22}^2 + c_{21}^2c_{22}^2 + e_{21}^2e_{22}^2}} & 1\end{bmatrix}$$

$$= \begin{bmatrix}1 & r_{Tr1Tr2}\\r_{Tr1Tr2} & 1\end{bmatrix}$$

This is repeated with the A, C and E variance components (e.g. the genetic correlation matrix is computed by (solve(sqrt(I*A))%&%A). The variance-covariance matrix is then formed by adding the standardised variance matrices (A, C and E) for both MZ and DZ twins:

$$MZ = \begin{bmatrix}A + C + E & A + C\\A + C & A + C + E\end{bmatrix}$$

$$DZ = \begin{bmatrix} A + C + E & 0.5 \times A + C \\ 0.5 \times A + C & A + C + E \end{bmatrix}$$

As each letter represents a matrix, the result is a 4 by 4 variance-covariance matrix as shown at the start of this section, decomposed into the variance components. For example, the variance-covariance matrix for MZ twins is:

$$\begin{bmatrix} a_{11}^2 + c_{11}^2 + e_{11}^2 & a_{21}a_{22} + c_{21}c_{22} + e_{21}e_{22} & a_{11}^2 + c_{11}^2 & a_{21}a_{22} + c_{21}c_{22} \\ a_{21}a_{22} + c_{21}c_{22} + e_{21}e_{22} & a_{21}^2a_{22}^2 + c_{21}^2c_{22}^2 + e_{21}^2e_{22}^2 & a_{21}a_{22} + c_{21}c_{22} & a_{21}^2a_{22}^2 + c_{21}^2c_{22}^2 \\ a_{11}^2 + c_{11}^2 & a_{21}a_{22} + c_{21}c_{22} & a_{11}^2 + c_{11}^2 + e_{11}^2 & a_{21}a_{22} + c_{21}c_{22} + e_{21}e_{22} \\ a_{21}a_{22} + c_{21}c_{22} & a_{21}^2a_{22}^2 + c_{21}^2c_{22}^2 & a_{21}a_{22} + c_{21}c_{22} + e_{21}e_{22} & a_{21}^2a_{22}^2 + c_{21}^2c_{22}^2 + e_{21}^2e_{22}^2 \end{bmatrix}$$

Appendix 4.1 Correlations (95% confidence intervals) and number of complete twin pairs between the 14 positive measures and the related measures involving relationships (a), personality (b), the five subscales of school engagement (c), and the five subscales of the strengths and difficulties questionnaire (d)

(a) Relationships	Life S.	Happ.	Rel.	Aut.	Comp.	Grat.	Opt.	Mean.	Trust	Hope.	Amb.	Grit	Cur.	Health
Peer attachment	0.55 (0.53, 0.57) 2069	0.43 (0.41, 0.46) 2071	0.56 (0.53, 0.58) 1014	0.44 (0.40, 0.47) 1014	0.38 (0.34, 0.41) 1014	0.39 (0.37, 0.42) 2057	0.31 (0.28, 0.34) 1990	0.31 (0.25, 0.36) 3592	0.32 (0.29, 0.36) 1009	0.33 (0.30, 0.35) 2055	0.20 (0.17, 0.23) 1989	0.23 (0.20, 0.26) 1992	0.15 (0.12, 0.18) 2051	0.17 (0.15, 0.20) 2061
Parental control	-0.03 (-0.01, 0.06) 2127	0.01 (-0.02, 0.04) 2129	0.02 (-0.03, 0.06) 1045	0.11 (0.07, 0.16) 1045	-0.02 (-0.07, 0.02) 1045	-0.04 (-0.07, -0.01) 2113	-0.03 (-0.06, 0.00) 2043	-0.05 (-0.11, 0.02) 3592	-0.07 (-0.11, -0.02) 1038	0.01 (-0.02, 0.04) 2113	-0.03 (-0.06, 0.00) 2042	-0.04 (-0.07, -0.01) 2045	-0.04 (-0.07, -0.01) 2106	-0.05 (-0.08, -0.02) 2119
Parental monitoring	0.37 (0.35, 0.40) 2112	0.27 (0.25, 0.30) 2114	0.25 (0.2, 0.28) 1035	0.26 (0.22, 0.30) 1035	0.26 (0.22, 0.30) 1035	0.32 (0.29, 0.34) 2098	0.20 (0.17, 0.23) 2030	0.16 (0.10, 0.22) 3592	0.22 (0.18, 0.26) 1028	0.22 (0.19, 0.25) 2098	0.19 (0.16, 0.22) 2029	0.25 (0.22, 0.28) 2032	0.05 (0.02, 0.08) 2091	0.15 (0.12, 0.18) 2104

(b) Personality	Life S.	Happ.	Rel.	Aut.	Comp.	Grat.	Opt.	Mean.	Trust	Hope.	Amb.	Grit	Cur.	Health
Neuroticism	-0.51 (-0.53, -0.48) 2040	-0.56 (-0.58, -0.54) 2042	-0.40 (-0.43, -0.37) 1013	-0.42 (-0.45, -0.39) 1013	-0.42 (-0.45, -0.39) 1013	-0.31 (-0.34, -0.29) 2028	-0.49 (-0.51, -0.46) 2039	-0.36 (-0.41, -0.30) 3592	-0.38 (-0.41, -0.34) 1007	-0.42 (-0.44, -0.39) 2029	-0.21 (-0.24, -0.18) 2038	-0.28 (-0.31, -0.26) 2041	-0.14 (-0.17, -0.11) 2022	-0.28 (-0.30, -0.25) 2034
Extraversion	0.37 (0.34, 0.40) 2037	0.44 (0.42, 0.47) 2039	0.44 (0.41, 0.47) 1011	0.31 (0.28, 0.35) 1011	0.34 (0.3, 0.37) 1011	0.32 (0.29, 0.34) 2025	0.32 (0.29, 0.34) 2036	0.20 (0.14, 0.26) 3592	0.34 (0.31, 0.38) 1005	0.36 (0.34, 0.39) 2026	0.32 (0.29, 0.35) 2035	0.21 (0.18, 0.24) 2038	0.29 (0.27, 0.32) 2019	0.24 (0.21, 0.27) 2031
Openness	0.04 (0.01, 0.08) 2033	0.07 (0.04, 0.09) 2035	0.06 (0.02, 0.10) 1009	0.03 (-0.01, 0.08) 1009	0.02 (-0.03, 0.06) 1009	0.13 (0.10, 0.16) 2021	0.07 (0.04, 0.10) 2032	0.01 (-0.06, 0.07) 3592	0.08 (0.03, 0.12) 1003	0.13 (0.10, 0.16) 2022	0.14 (0.11, 0.17) 2032	-0.02 (-0.05, 0.01) 2035	0.25 (0.22, 0.27) 2015	-0.02 (-0.05, 0.01) 2027
Agreeableness	0.24 (0.21, 0.27) 2026	0.21 (0.19, 0.24) 2028	0.23 (0.19, 0.27) 1008	0.11 (0.06, 0.15) 1008	0.11 (0.06, 0.15) 1008	0.31 (0.28, 0.34) 2014	0.12 (0.10, 0.15) 2025	0.21 (0.15, 0.27) 3592	0.12 (0.08, 0.16) 1002	0.11 (0.08, 0.14) 2015	0.10 (0.07, 0.13) 2025	0.19 (0.16, 0.22) 2028	0.02 (-0.01, 0.05) 2008	0.08 (0.05, 0.11) 2020
Conscientiousness	0.31 (0.28, 0.34) 2023	0.18 (0.15, 0.20) 2025	0.22 (0.18, 0.26) 1007	0.21 (0.16, 0.25) 1007	0.33 (0.29, 0.37) 1007	0.32 (0.29, 0.35) 2011	0.21 (0.18, 0.24) 2022	0.07 (0.01, 0.14) 3592	0.29 (0.25, 0.33) 1001	0.36 (0.33, 0.38) 2012	0.47 (0.44, 0.49) 2022	0.49 (0.47, 0.51) 2025	0.26 (0.23, 0.29) 2005	0.17 (0.14, 0.20) 2017

(c) School Engagement	Life S.	Happ.	Rel.	Aut.	Comp.	Grat.	Opt.	Mean.	Trust	Hope.	Amb.	Grit	Cur.	Health
Teacher-Student Relationship	0.26 (0.23, 0.28) 2235	0.12 (0.10, 0.15) 2238	0.13 (0.09, 0.17) 1083	0.10 (0.06, 0.14) 1083	0.15 (0.11, 0.19) 1083	0.19 (0.16, 0.21) 2221	0.16 (0.14, 0.19) 2063	0.18 (0.12, 0.24) 3592	0.11 (0.07, 0.15) 1075	0.17 (0.14, 0.20) 2221	0.15 (0.12, 0.18) 2061	0.11 (0.08, 0.14) 2064	0.10 (0.08, 0.13) 2212	0.13 (0.10, 0.16) 2227
Sense of control and relevance of schoolwork	0.27 (0.24, 0.29) 2233	0.15 (0.13, 0.18) 2235	0.14 (0.10, 0.18) 1082	0.14 (0.10, 0.18) 1082	0.22 (0.18, 0.25) 1082	0.23 (0.20, 0.25) 2218	0.17 (0.14, 0.20) 2061	0.15 (0.09, 0.21) 3592	0.19 (0.15, 0.23) 1074	0.22 (0.19, 0.25) 2218	0.22 (0.20, 0.25) 2059	0.20 (0.17, 0.23) 2062	0.17 (0.15, 0.20) 2209	0.12 (0.09, 0.15) 2224
Peer support for learning	0.33 (0.30, 0.35) 2229	0.24 (0.21, 0.27) 2231	0.28 (0.24, 0.31) 1079	0.20 (0.16, 0.24) 1079	0.22 (0.18, 0.26) 1079	0.23 (0.20, 0.26) 2214	0.20 (0.17, 0.23) 2058	0.23 (0.17, 0.28) 3592	0.19 (0.15, 0.23) 1071	0.22 (0.19, 0.25) 2214	0.14 (0.11, 0.17) 2056	0.12 (0.09, 0.15) 2059	0.11 (0.08, 0.14) 2205	0.15 (0.12, 0.18) 2220
Future aspirations and goals	0.14 (0.11, 0.17) 2229	0.07 (0.04, 0.09) 2231	0.08 (0.04, 0.12) 1079	0.05 (0.01, 0.09) 1079	0.10 (0.06, 0.14) 1079	0.14 (0.11, 0.17) 2214	0.10 (0.07, 0.13) 2057	0.08 (0.02, 0.14) 3592	0.10 (0.06, 0.14) 1071	0.11 (0.08, 0.14) 2214	0.14 (0.11, 0.17) 2055	0.08 (0.05, 0.11) 2058	0.07 (0.04, 0.10) 2205	0.08 (0.05, 0.10) 2220
Family support for learning	0.18 (0.16, 0.21) 2225	0.10 (0.07, 0.13) 2227	0.12 (0.08, 0.16) 1077	0.10 (0.06, 0.14) 1077	0.14 (0.10, 0.18) 1077	0.17 (0.14, 0.20) 2210	0.10 (0.07, 0.13) 2053	-0.07 (-0.13, -0.01) 3592	0.11 (0.07, 0.15) 1069	0.09 (0.07, 0.12) 2210	0.09 (0.06, 0.12) 2051	0.07 (0.04, 0.10) 2054	0.05 (0.02, 0.08) 2201	0.09 (0.06, 0.12) 2216
Total school engagement	0.27 (0.24, 0.30) 2232	0.15 (0.12, 0.18) 2234	0.17 (0.13, 0.20) 1081	0.13 (0.09, 0.17) 1081	0.19 (0.15, 0.23) 1081	0.22 (0.19, 0.25) 2217	0.17 (0.14, 0.20) 2060	0.16 (0.10, 0.22) 3592	0.16 (0.12, 0.19) 1073	0.19 (0.16, 0.21) 2217	0.17 (0.14, 0.20) 2058	0.13 (0.10, 0.16) 2061	0.12 (0.09, 0.15) 2208	0.13 (0.10, 0.16) 2223

(d) Strengths and Difficulties Questionnaire	Life S.	Happ.	Rel.	Aut.	Comp.	Grat.	Opt.	Mean.	Trust	Hope.	Amb.	Grit	Cur.	Health
Anxiety/ emotional problems	-0.48 (-0.49, -0.46) 4768	-0.43 (-0.45, -0.42) 4760	-0.34 (-0.36, -0.32) 3710	-0.45 (-0.47, -0.44) 3710	-0.43 (-0.45, -0.41) 3706	-0.15 (-0.18, -0.11) 1879	-0.36 (-0.39, -0.33) 1706	-0.35 (-0.37, -0.32) 3592	-0.33 (-0.35, -0.31) 3701	-0.31 (-0.34, -0.28) 1878	-0.11 (-0.14, -0.08) 1704	-0.17 (-0.20, -0.14) 1707	-0.09 (-0.12, -0.06) 1871	-0.27 (-0.29, -0.24) 1883
Peer relationship problems	-0.48 (-0.50, -0.47) 4767	-0.41 (-0.43, -0.39) 4759	-0.66 (-0.67, -0.64) 3709	-0.43 (-0.44, -0.41) 3709	-0.36 (-0.38, -0.34) 3705	-0.27 (-0.30, -0.24) 1878	-0.27 (-0.30, -0.24) 1705	-0.33 (-0.36, -0.30) 3592	-0.30 (-0.32, -0.28) 3701	-0.24 (-0.27, -0.21) 1877	-0.10 (-0.13, -0.07) 1703	-0.15 (-0.18, -0.11) 1706	-0.02 (-0.05, 0.01) 1870	-0.20 (-0.23, -0.17) 1882
Hyperactivity/ inattention	-0.33 (-0.34, -0.31) 4767	-0.20 (-0.22, -0.18) 4758	-0.23 (-0.25, -0.21) 3709	-0.29 (-0.31, -0.27) 3709	-0.39 (-0.41, -0.37) 3705	-0.22 (-0.25, -0.19) 1878	-0.25 (-0.28, -0.22) 1705	-0.26 (-0.29, -0.23) 3592	-0.27 (-0.29, -0.24) 3701	-0.27 (-0.30, -0.24) 1877	-0.23 (-0.26, -0.20) 1703	-0.42 (-0.45, -0.39) 1706	-0.05 (-0.09, -0.02) 1870	-0.20 (-0.23, -0.17) 1882
Conduct problems	-0.36 (-0.38, -0.35) 4766	-0.28 (-0.30, -0.26) 4757	-0.26 (-0.28, -0.24) 3710	-0.26 (-0.28, -0.24) 3710	-0.31 (-0.33, -0.28) 3706	-0.28 (-0.31, -0.25) 1878	-0.23 (-0.26, -0.19) 1705	-0.28 (-0.31, -0.25) 3592	-0.22 (-0.24, -0.20) 3701	-0.19 (-0.22, -0.16) 1877	-0.14 (-0.18, -0.11) 1703	-0.27 (-0.30, -0.23) 1706	0.01 (-0.03, 0.04) 1870	-0.18 (-0.22, -0.15) 1882
Total behavioural difficulties	-0.60 (-0.61, -0.58) 4769	-0.48 (-0.49, -0.46) 4760	-0.52 (-0.53, -0.50) 3710	-0.52 (-0.54, -0.51) 3710	-0.55 (-0.57, -0.54) 3706	-0.32 (-0.35, -0.29) 1879	-0.41 (-0.44, -0.39) 1706	-0.45 (-0.48, -0.42) 3592	-0.41 (-0.43, -0.39) 3701	-0.39 (-0.41, -0.36) 1878	-0.22 (-0.25, -0.19) 1704	-0.38 (-0.41, -0.35) 1707	-0.07 (-0.10, -0.04) 1871	-0.32 (-0.35, -0.29) 1883
Prosocial behaviour	0.26 (0.24, 0.28) 4766	0.28 (0.26, 0.30) 4757	0.39 (0.37, 0.41) 3710	0.24 (0.22, 0.26) 3710	0.30 (0.28, 0.32) 3706	0.38 (0.35, 0.40) 1878	0.16 (0.12, 0.19) 1705	0.21 (0.18, 0.25) 3592	0.29 (0.27, 0.32) 3701	0.23 (0.20, 0.26) 1877	0.21 (0.18, 0.24) 1703	0.26 (0.22, 0.29) 1706	0.20 (0.16, 0.23) 1870	0.10 (0.07, 0.13) 1882

Note: Life S. = Life Satisfaction; Rel. = Relatedness; Aut. = Autonomy; Comp. = Competence; Happ. = Subjective Happiness; Mean. = Meaning in Life; Grat. = Gratitude; Opt. = Optimism; Hope. = Hopefulness; Amb. = Ambition; Cur. = Curiosity, Health = Subjective Health. Number of complete pairs of twins is given with each correlation. Colour of cell indicates strength of correlation, with blue indicating a correlation of -1, white no correlation and red a correlation of 1. Relatedness, autonomy, competence, meaning in life and trust were collected on the booklet. Gratitude, optimism, hopefulness, ambition, grit, curiosity and subjective health were collected on the web.

Appendix 5.1 Model comparisons for the saturated model and the ACE model, for each of the wellbeing indicators

	Base model	Comparison	EP	-2 Log likelihood	Degrees of freedom	Δ-2LL	Δdf	*p*
Subjective wellbeing indicators								
Life satisfaction	Saturated		9	25906.45	9621			
	Saturated	ACE	6	25909.09	9624	2.64	3	0.45
Subjective happiness	Saturated		9	26204.49	9615			
	Saturated	ACE	6	26206.76	9618	2.26	3	0.52
Eudaimonic wellbeing indicators								
Relatedness (b)	Saturated		9	20520.60	7432			
	Saturated	ACE	6	20527.64	7435	7.04	3	0.07
Autonomy (b)	Saturated		9	20697.14	7432			
	Saturated	ACE	6	20697.80	7435	0.67	3	0.88
Competence (b)	Saturated		9	20676.14	7428			
	Saturated	ACE	6	20679.62	7431	3.48	3	0.32
Gratitude (w)	Saturated		9	13509.54	4876			
	Saturated	ACE	6	13513.23	4879	3.68	3	0.30
Optimism (w)	Saturated		9	12391.70	4437			
	Saturated	ACE	6	12393.86	4440	2.17	3	0.54
Meaning in life (b)	Saturated		9	20578.06	7415			
	Saturated	ACE	6	20583.68	7418	5.62	3	0.13
Trust (b)	Saturated		8	6471.17	7344			
	Saturated	ACE	6	6474.23	7348	3.06	4	0.55
Hopefulness (w)	Saturated		9	13267.11	4863			
	Saturated	ACE	6	13272.38	4866	5.27	3	0.15
Ambition (w)	Saturated		9	12360.37	4435			
	Saturated	ACE	6	12363.05	4438	2.68	3	0.44
Grit (w)	Saturated		9	12412.88	4438			
	Saturated	ACE	6	12414.28	4441	1.40	3	0.71
Curiosity (w)	Saturated		9	13518.66	4865			
	Saturated	ACE	6	13523.90	4868	5.25	3	0.15
Subjective Health (w)	Saturated		9	13643.09	4883			
	Saturated	ACE	6	13645.24	4886	2.15	3	0.54

Note. EP refers to number of estimated parameters in model, Δ-2LL refers to difference in Log likelihood, Δdf refers to difference in degrees of freedom. Wellbeing indicators with (b) were measured on the booklet data collection, and indicators with (w) were measured on the web data collection.

Appendix 5.2 The genetic (A), shared environment (C) and nonshared environment (E) univariate parameter estimates with 95% confidence intervals for the two subjective wellbeing indicators and the 12 eudaimonic wellbeing indicators

	Twin model estimates		
	A	C	E
Subjective wellbeing indicators			
Life Satisfaction	0.46 (0.38; 0.54)	0.10 (0.04; 0.16)	0.44 (0.42; 0.47)
Subjective Happiness	0.41 (0.36; 0.44)	0.00 (0.00; 0.03)	0.59 (0.56; 0.62)
Eudaimonic wellbeing indicators			
Relatedness (b)	0.49 (0.45; 0.52)	0.00 (0.00; 0.04)	0.51 (0.48; 0.55)
Autonomy (b)	0.44 (0.35; 0.48)	0.00 (0.00; 0.07)	0.56 (0.52; 0.59)
Competence (b)	0.45 (0.39; 0.49)	0.00 (0.00; 0.04)	0.55 (0.51; 0.58)
Gratitude (w)	0.36 (0.22; 0.45)	0.04 (0.00; 0.15)	0.60 (0.55; 0.65)
Optimism (w)	0.37 (0.32; 0.42)	0.00 (0.00; 0.09)	0.63 (0.58; 0.68)
Meaning in life (b)	0.46 (0.40; 0.50)	0.00 (0.00; 0.04)	0.54 (0.50; 0.57)
Trust (b)	0.54 (0.40; 0.62)	0.00 (0.00; 0.11)	0.46 (0.38; 0.54)
Hopefulness (w)	0.35 (0.21; 0.40)	0.00 (0.00; 0.11)	0.65 (0.60; 0.70)
Ambition (w)	0.41 (0.32; 0.45)	0.00 (0.00; 0.06)	0.59 (0.55; 0.65)
Grit (w)	0.38 (0.33; 0.43)	0.00 (0.00; 0.10)	0.62 (0.57; 0.67)
Curiosity (w)	0.39 (0.32; 0.44)	0.00 (0.00; 0.06)	0.61 (0.56; 0.66)
Subjective Health (w)	0.33 (0.22; 0.38)	0.00 (0.00; 0.08)	0.67 (0.62; 0.72)

Note. (b) indicates measures collected on the booklet, (w) indicates measures collected on the web.

Appendix 5.3 The genetic correlation (rA) estimates (95% CI) in the upper triangle and the proportion of phenotypic variation explained by genetic influences (95% CI) in the lower triangle for the 14 measures

	Life S.	Happ.	Rel.	Aut.	Comp.	Grat.	Opt.	Mean.	Trust	Hope.	Amb.	Grit	Cur.	Health
Life Satisfaction		0.85 (0.79, 0.93)	0.79 (0.72, 0.86)	0.69 (0.61, 0.77)	0.78 (0.71, 0.87)	0.82 (0.69, 0.96)	0.73 (0.59, 0.90)	0.74 (0.66, 0.83)	0.64 (0.47, 0.86)	0.82 (0.69, 0.97)	0.39 (0.23, 0.54)	0.49 (0.33, 0.67)	0.24 (0.05, 0.41)	0.59 (0.45, 0.74)
Subjective Happiness	0.57 (0.47, 0.64)		0.74 (0.7, 0.79)	0.71 (0.65, 0.76)	0.74 (0.69, 0.79)	0.68 (0.58, 0.83)	0.67 (0.6, 0.81)	0.68 (0.63, 0.73)	0.52 (0.43, 0.78)	0.69 (0.62, 0.83)	0.37 (0.28, 0.45)	0.43 (0.35, 0.59)	0.29 (0.20, 0.38)	0.55 (0.46, 0.63)
Relatedness	0.56 (0.46, 0.65)	0.61 (0.56, 0.65)		0.79 (0.78, 0.87)	0.76 (0.72, 0.84)	0.65 (0.52, 0.81)	0.60 (0.49, 0.77)	0.65 (0.60, 0.71)	0.57 (0.49, 0.79)	0.66 (0.54, 0.93)	0.42 (0.30, 0.55)	0.42 (0.26, 0.59)	0.22 (0.09, 0.37)	0.49 (0.35, 0.64)
Autonomy	0.50 (0.38, 0.61)	0.61 (0.55, 0.66)	0.57 (0.48, 0.62)		0.83 (0.79, 0.88)	0.54 (0.37, 0.78)	0.60 (0.47, 0.84)	0.61 (0.55, 0.71)	0.54 (0.43, 0.74)	0.58 (0.45, 0.87)	0.35 (0.22, 0.54)	0.35 (0.15, 0.55)	0.21 (0.06, 0.40)	0.41 (0.23, 0.61)
Competence	0.59 (0.48, 0.69)	0.63 (0.58, 0.68)	0.6 (0.53, 0.65)	0.59 (0.49, 0.64)		0.61 (0.48, 0.80)	0.70 (0.59, 0.88)	0.81 (0.78, 0.86)	0.54 (0.45, 0.70)	0.87 (0.76, 1.00)	0.64 (0.54, 0.93)	0.66 (0.53, 0.94)	0.39 (0.28, 0.60)	0.46 (0.34, 0.67)
Gratitude	0.61 (0.46, 0.72)	0.56 (0.42, 0.65)	0.66 (0.46, 0.8)	0.64 (0.39, 0.86)	0.67 (0.47, 0.82)		0.69 (0.52, 0.96)	0.62 (0.49, 0.83)	0.52 (0.25, 0.96)	0.65 (0.50, 0.80)	0.44 (0.24, 0.58)	0.44 (0.24, 0.65)	0.40 (0.22, 0.57)	0.42 (0.19, 0.59)
Optimism	0.59 (0.41, 0.73)	0.56 (0.45, 0.64)	0.67 (0.50, 0.80)	0.64 (0.45, 0.81)	0.64 (0.51, 0.76)	0.67 (0.42, 0.88)		0.67 (0.57, 0.91)	0.53 (0.33, 0.75)	0.66 (0.52, 0.85)	0.58 (0.48, 0.77)	0.51 (0.31, 0.66)	0.28 (0.13, 0.44)	0.54 (0.38, 0.75)

Appendix 5.3 (continued) The genetic correlation (rA) estimates (95% CI) in the upper triangle and the proportion of phenotypic variation explained by genetic influences (95% CI) in the lower triangle for the 14 measures

	Life S.	Happ.	Rel.	Aut.	Comp.	Grat.	Opt.	Mean.	Trust	Hope.	Amb.	Grit	Cur.	Health
Meaning in life	0.57 (0.46, 0.66)	0.56 (0.50, 0.61)	0.62 (0.53, 0.67)	0.57 (0.46, 0.63)	0.60 (0.59, 0.65)	0.66 (0.47, 0.82)	0.67 (0.53, 0.81)		0.44 (0.35, 0.61)	0.91 (0.69, 1.00)	0.59 (0.49, 0.73)	0.57 (0.41, 0.88)	0.44 (0.32, 0.66)	0.39 (0.24, 0.55)
Trust	0.73 (0.50, 0.92)	0.66 (0.53, 0.79)	0.66 (0.53, 0.79)	0.68 (0.49, 0.84)	0.71 (0.54, 0.84)	0.90 (0.42, 1.00)	0.62 (0.33, 0.82)	0.61 (0.45, 0.76)		0.42 (0.20, 0.82)	0.33 (0.16, 0.59)	0.31 (0.09, 0.61)	0.29 (0.11, 0.56)	0.36 (0.17, 0.74)
Hopefulness	0.56 (0.43, 0.66)	0.54 (0.47, 0.60)	0.75 (0.56, 0.93)	0.62 (0.42, 0.81)	0.74 (0.61, 0.86)	0.48 (0.28, 0.62)	0.54 (0.33, 0.65)	0.68 (0.54, 0.79)	0.81 (0.36, 1.00)		0.73 (0.63, 0.86)	0.70 (0.55, 0.97)	0.57 (0.45, 0.71)	0.57 (0.37, 0.71)
Ambition	0.47 (0.24, 0.68)	0.61 (0.48, 0.74)	0.70 (0.50, 0.88)	0.67 (0.40, 0.93)	0.76 (0.64, 0.96)	0.45 (0.19, 0.67)	0.66 (0.49, 0.81)	0.61 (0.50, 0.72)	0.96 (0.49, 1.00)	0.57 (0.40, 0.64)		0.62 (0.48, 0.73)	0.61 (0.52, 0.70)	0.41 (0.28, 0.59)
Grit	0.55 (0.32, 0.79)	0.71 (0.57, 0.83)	0.65 (0.37, 0.85)	0.51 (0.20, 0.73)	0.66 (0.51, 0.83)	0.54 (0.23, 0.77)	0.53 (0.24, 0.65)	0.68 (0.49, 0.90)	0.59 (0.17, 1.00)	0.65 (0.44, 0.80)	0.55 (0.32, 0.63)		0.35 (0.21, 0.53)	0.49 (0.33, 0.81)
Curiosity	0.42 (0.09, 0.73)	0.54 (0.40, 0.68)	0.67 (0.30, 1.00)	0.72 (0.21, 1.00)	0.68 (0.48, 0.92)	0.52 (0.24, 0.72)	0.53 (0.22, 0.77)	0.62 (0.47, 0.83)	0.76 (0.52; 0.99)*	0.48 (0.31, 0.57)	0.53 (0.51, 0.60)	0.66 (0.34, 0.90)		0.16 (-0.06, 0.29)
Health	0.54 (0.35, 0.73)	0.61 (0.45, 0.70)	0.70 (0.46, 0.87)	0.71 (0.35, 0.97)	0.63 (0.44, 0.83)	0.48 (0.17, 0.74)	0.68 (0.40, 0.86)	0.57 (0.32, 0.74)	0.86 (0.39, 1.00)	0.53 (0.26, 0.69)	0.71 (0.43, 0.93)	0.78 (0.48, 1.00)	0.48 (-0.16, 0.80)	

Note: Life S. = Life Satisfaction; Rel. = Relatedness; Aut. = Autonomy; Comp. = Competence; Happ. = Subjective Happiness; Mean. = Meaning in Life; Grat. = Gratitude; Opt. = Optimism; Hope. = Hopefulness; Amb. = Ambition; Cur. = Curiosity, Health = Subjective Health. Number of complete pairs of twins ranged from 1010 to 5269. The proportions for curiosity and trust were calculated using absolute values, as the nonshared environmental correlation was negative.

Appendix 5.4 The nonshared environmental correlation (rE) estimates (95% CI) in the upper triangle and the proportion of phenotypic variation explained by nonshared environmental influences (95% CI) in the lower triangle for the 14 measures

	Life S.	Happ.	Rel.	Aut.	Comp.	Grat.	Opt.	Mean.	Trust	Hope.	Amb.	Grit	Cur.	Health
Life Satisfaction		0.47 (0.44, 0.51)	0.48 (0.44, 0.52)	0.47 (0.43, 0.50)	0.39 (0.35, 0.43)	0.42 (0.37, 0.47)	0.34 (0.28, 0.40)	0.44 (0.40, 0.48)	0.29 (0.21, 0.37)	0.47 (0.42, 0.51)	0.25 (0.18, 0.31)	0.21 (0.14, 0.27)	0.22 (0.15, 0.27)	0.23 (0.17, 0.28)
Subjective Happiness	0.38 (0.35, 0.42)		0.40 (0.36, 0.43)	0.35 (0.30, 0.38)	0.34 (0.30, 0.38)	0.35 (0.31, 0.40)	0.34 (0.29, 0.39)	0.43 (0.39, 0.46)	0.26 (0.18, 0.34)	0.37 (0.33, 0.41)	0.16 (0.10, 0.21)	0.12 (0.07, 0.17)	0.16 (0.11, 0.21)	0.20 (0.16, 0.25)
Relatedness	0.36 (0.32, 0.40)	0.39 (0.35, 0.44)		0.51 (0.49, 0.54)	0.45 (0.41, 0.47)	0.23 (0.15, 0.31)	0.22 (0.14, 0.30)	0.36 (0.32, 0.40)	0.31 (0.23, 0.38)	0.16 (0.08, 0.24)	0.14 (0.06, 0.23)	0.17 (0.08, 0.26)	0.09 (0.00, 0.17)	0.15 (0.06, 0.23)
Autonomy	0.40 (0.36, 0.45)	0.39 (0.34, 0.45)	0.43 (0.40, 0.44)		0.46 (0.42, 0.48)	0.20 (0.16, 0.28)	0.23 (0.15, 0.30)	0.39 (0.35, 0.43)	0.25 (0.17, 0.32)	0.24 (0.16, 0.31)	0.13 (0.05, 0.21)	0.23 (0.15, 0.31)	0.06 (-0.02, 0.14)	0.11 (0.02, 0.19)
Competence	0.33 (0.29, 0.38)	0.37 (0.32, 0.42)	0.40 (0.35, 0.45)	0.41 (0.36, 0.45)		0.21 (0.13, 0.29)	0.27 (0.20, 0.34)	0.45 (0.42, 0.49)	0.22 (0.15, 0.30)	0.21 (0.13, 0.28)	0.16 (0.08, 0.23)	0.24 (0.16, 0.32)	0.14 (0.06, 0.22)	0.17 (0.09, 0.25)
Gratitude	0.37 (0.31, 0.42)	0.44 (0.37, 0.50)	0.30 (0.20, 0.41)	0.33 (0.20, 0.46)	0.31 (0.20, 0.43)		0.18 (0.12, 0.24)	0.23 (0.15, 0.30)	0.10 (-0.04, 0.24)	0.37 (0.32, 0.42)	0.25 (0.19, 0.31)	0.20 (0.14, 0.26)	0.21 (0.16, 0.27)	0.18 (0.12, 0.23)
Optimism	0.37 (0.30, 0.44)	0.44 (0.38, 0.51)	0.33 (0.21, 0.45)	0.36 (0.24, 0.48)	0.36 (0.26, 0.45)	0.30 (0.20, 0.40)		0.24 (0.16, 0.31)	0.28 (0.14, 0.41)	0.33 (0.27, 0.38)	0.19 (0.13, 0.25)	0.27 (0.21, 0.33)	0.15 (0.10, 0.21)	0.14 (0.08, 0.20)

Appendix 5.4 (continued) The nonshared environmental correlation (rE) estimates (95% CI) in the upper triangle and the proportion of phenotypic variation explained by nonshared environmental influences (95% CI) in the lower triangle for the 14 measures

	Life S.	Happ.	Rel.	Aut.	Comp.	Grat.	Opt.	Mean.	Trust	Hope.	Amb.	Grit	Cur.	Health
Meaning	0.37 (0.33, 0.42)	0.44 (0.39, 0.50)	0.38 (0.33, 0.44)	0.43 (0.38, 0.49)	0.40 (0.36, 0.44)	0.32 (0.22, 0.43)	0.33 (0.23, 0.43)		0.28 (0.21, 0.36)	0.30 (0.23, 0.37)	0.29 (0.21, 0.35)	0.20 (0.12, 0.27)	0.20 (0.12, 0.27)	0.19 (0.12, 0.27)
Trust	0.30 (0.22, 0.39)	0.34 (0.26, 0.43)	0.34 (0.26, 0.43)	0.32 (0.22, 0.43)	0.29 (0.19, 0.40)	0.20 (-0.09, 0.47)	0.38 (0.20, 0.57)	0.39 (0.29, 0.50)		0.09 (-0.05, 0.23)	0.01 (-0.13, 0.15)	0.18 (0.04, 0.33)	-0.07 (-0.21, 0.07)	0.05 (-0.09, 0.18)
Hopefulness	0.43 (0.37, 0.48)	0.46 (0.40, 0.53)	0.25 (0.12, 0.37)	0.38 (0.26, 0.50)	0.26 (0.17, 0.35)	0.46 (0.39, 0.54)	0.46 (0.38, 0.55)	0.35 (0.27, 0.44)	0.21 (-0.12, 0.51)		0.35 (0.30, 0.40)	0.23 (0.17, 0.29)	0.38 (0.34, 0.43)	0.23 (0.17, 0.28)
Ambition	0.38 (0.28, 0.48)	0.39 (0.26, 0.52)	0.30 (0.12, 0.47)	0.33 (0.13, 0.54)	0.24 (0.12, 0.36)	0.43 (0.32, 0.54)	0.34 (0.23, 0.44)	0.39 (0.29, 0.49)	0.04 (-0.49, 0.47)	0.43 (0.36, 0.51)		0.33 (0.28, 0.38)	0.36 (0.31, 0.41)	0.10 (0.04, 0.16)
Grit	0.30 (0.21, 0.40)	0.29 (0.17, 0.43)	0.35 (0.18, 0.53)	0.49 (0.32, 0.66)	0.35 (0.23, 0.45)	0.40 (0.28, 0.52)	0.47 (0.37, 0.58)	0.34 (0.20, 0.47)	0.41 (0.09, 0.73)	0.37 (0.27, 0.46)	0.45 (0.37, 0.54)		0.12 (0.06, 0.17)	0.09 (0.02, 0.14)
Curiosity	0.48 (0.34, 0.63)	0.46 (0.32, 0.60)	0.33 (-0.01, 0.68)	0.28 (-0.11, 0.67)	0.32 (0.14, 0.51)	0.43 (0.32, 0.56)	0.47 (0.30, 0.66)	0.38 (0.23, 0.52)	0.24 (0.00; 0.42)*	0.52 (0.44, 0.60)	0.47 (0.40, 0.55)	0.34 (0.17, 0.51)		0.10 (0.04, 0.15)
Health	0.31 (0.23, 0.40)	0.39 (0.30, 0.49)	0.30 (0.13, 0.47)	0.29 (0.07, 0.50)	0.37 (0.20, 0.53)	0.39 (0.27, 0.52)	0.32 (0.19, 0.46)	0.43 (0.27, 0.60)	0.14 (-0.33, 0.53)	0.42 (0.32, 0.53)	0.29 (0.13, 0.46)	0.25 (0.07, 0.42)	0.52 (0.24, 0.83)	

Note: Life S. = Life Satisfaction; Rel. = Relatedness; Aut. = Autonomy; Comp. = Competence; Happ. = Subjective Happiness; Mean. = Meaning in Life; Grat. = Gratitude; Opt. = Optimism; Hope. = Hopefulness; Amb. = Ambition; Cur. = Curiosity, Health = Subjective Health. Number of complete pairs of twins ranged from 1010 to 5269. The proportions for curiosity and trust were calculated using absolute values, as the nonshared environmental correlation was negative.

* The proportions for curiosity were calculated using absolute values, as the non-shared environmental correlation was negative.

Appendix 7.1 Example R code loop for assigning physical environment characteristics to each TEDS family

```
# Loop to create scenic score for each TEDS family, for every km
circular area of their location up to 20km radius

# 1) install relevant package
# install.packages("geosphere")
library(geosphere)

# 2) Create relevant dataframes
# check dataframes for twin location and for scenic locations
str(twinData)
str(OSugs)


# create dataframes to hold data
km1 <- c()
km2 <- c()
km3 <- c()
km4 <- c()
km5 <- c()
km6 <- c()
km7 <- c()
km8 <- c()
km9 <- c()
km10 <- c()
km11 <- c()
km12 <- c()
km13 <- c()
km14 <- c()
km15 <- c()
km16 <- c()
km17 <- c()
km18 <- c()
km19 <- c()
km20 <- c()

distT <- c(1000, 2000, 3000, 4000, 5000, 6000, 7000, 8000, 9000,
10000, 11000, 12000, 13000, 14000, 15000, 16000, 17000, 18000,
19000, 20000)


start.time <- Sys.time()
```

```
for (i in 1:nrow(twinData)){
  twinLon <- twinData[i,"lon"]
  twinLat <- twinData[i,"lat"]
  twinLL <- c(twinLon, twinLat)
  rangeLat <- c(twinLat - 0.5, twinLat + 0.5)
  closeOS <- subset(OSugs, OSugs$lat > rangeLat[[1]] & OSugs$lat <
rangeLat[[2]])
  if(nrow(closeOS) == 0){ closeOS[1,] <- NA }
  closeOS$rows <- 1:nrow(closeOS)
  OSll <- data.frame(closeOS["long"], closeOS["lat"])
  distm <- (distHaversine(twinLL, OSll))
  for (z in 1:length(distT)) {
    rows <- which(distm < distT[z])
    values <- closeOS[rows, ]
    ifelse(nrow(values) == 0, meanDist <- NA, meanDist <-
mean(values$min.distm., na.rm = T))
    ifelse(nrow(values) == 0, minDist <- NA, minDist <-
min(values$min.distm., na.rm = T))
    ifelse(nrow(values) == 0, maxDist <- NA, maxDist <-
max(values$min.distm., na.rm = T))
    ifelse(nrow(values) == 0, meanScenic <- NA, meanScenic <-
mean(values$Average, na.rm = T))
    ifelse(nrow(values) == 0, minScenic <- NA, minScenic <-
min(values$Average, na.rm = T))
    ifelse(nrow(values) == 0, maxScenic <- NA, maxScenic <-
max(values$Average, na.rm = T))
    ifelse(nrow(values) == 0, meanUR <- NA, meanUR <-
mean(values$UR, na.rm = T))
    ifelse(nrow(values) == 0, minUR <- NA, minUR <- min(values$UR,
na.rm = T))
    ifelse(nrow(values) == 0, maxUR <- NA, maxUR <- max(values$UR,
na.rm = T))
    ifelse(nrow(values) == 0, meanG <- NA, meanG <-
mean(values$percGreen, na.rm = T))
    ifelse(nrow(values) == 0, minG <- NA, minG <-
min(values$percGreen, na.rm = T))
    ifelse(nrow(values) == 0, maxG <- NA, maxG <-
max(values$percGreen, na.rm = T))
    Npoints <- nrow(values)
    assign(paste("scenicKm", distT[z], sep = ""),
data.frame(twinData$id_fam[i], meanDist, minDist, maxDist,
meanScenic, minScenic, maxScenic, meanUR, minUR, maxUR, meanG, minG,
maxG,Npoints))
  }
  km1 <- rbind(km1, scenicKm1000)
  km2 <- rbind(km2, scenicKm2000)
  km3 <- rbind(km3, scenicKm3000)
  km4 <- rbind(km4, scenicKm4000)
  km5 <- rbind(km5, scenicKm5000)
```

```
  km6 <- rbind(km6, scenicKm6000)
  km7 <- rbind(km7, scenicKm7000)
  km8 <- rbind(km8, scenicKm8000)
  km9 <- rbind(km9, scenicKm9000)
  km10 <- rbind(km10, scenicKm10000)
  km11 <- rbind(km11, scenicKm11000)
  km12 <- rbind(km12, scenicKm12000)
  km13 <- rbind(km13, scenicKm13000)
  km14 <- rbind(km14, scenicKm14000)
  km15 <- rbind(km15, scenicKm15000)
  km16 <- rbind(km16, scenicKm16000)
  km17 <- rbind(km17, scenicKm17000)
  km18 <- rbind(km18, scenicKm18000)
  km19 <- rbind(km19, scenicKm19000)
  km20 <- rbind(km20, scenicKm20000)

  write.csv(km1, "UGS km1 studio.csv")
  write.csv(km2, "UGS km2 studio.csv")
  write.csv(km3, "UGS km3 studio.csv")
  write.csv(km4, "UGS km4 studio.csv")
  write.csv(km5, "UGS km5 studio.csv")
  write.csv(km6, "UGS km6 studio.csv")
  write.csv(km7, "UGS km7 studio.csv")
  write.csv(km8, "UGS km8 studio.csv")
  write.csv(km9, "UGS km9 studio.csv")
  write.csv(km10, "UGS km10 studio.csv")
  write.csv(km11, "UGS km11 studio.csv")
  write.csv(km12, "UGS km12 studio.csv")
  write.csv(km13, "UGS km13 studio.csv")
  write.csv(km14, "UGS km14 studio.csv")
  write.csv(km15, "UGS km15 studio.csv")
  write.csv(km16, "UGS km16 studio.csv")
  write.csv(km17, "UGS km17 studio.csv")
  write.csv(km18, "UGS km18 studio.csv")
  write.csv(km19, "UGS km19 studio.csv")
  write.csv(km20, "UGS km20 studio.csv")

}
end.time <- Sys.time()
(time.taken <- end.time - start.time)
```

Appendix 7.2 Summary of hierarchical regression analyses to understand the effect of a scenic environment on positive outcomes during adolescence, after controlling for urban-rural classification and green space (Distances 1 – 20 km)

1 km	**Subjective Happiness** (n = 4930)				**Life Satisfaction** (n = 4928)				**Subjective Health** (n = 2553)			
	β (95% CIs)	t-value (*p*)	R^2	F statistic	β (95% CIs)	t-value (*p*)	R^2	F statistic	β (95% CIs)	t-value (*p*)	R^2	F statistic
Model 1: Scenic only												
Scenic	0.01 (-0.02, 0.03)	0.78 (0.44)			0.03 (0.00, 0.05)	1.92 (0.05)			0.03 (0.00, 0.06)	1.99 (0.05)		
Model 1 statistics			0.01	F(1, 4862) = 0.61 *p* = 0.44			0.08	F(1, 4860) = 3.7 *p* = 0.05			0.16	F(1, 2527) = 3.98 *p* = 0.05
Model 2: Urban-rural classification + green space												
Urban-rural classification	0.00 (-0.02, 0.01)	-0.17 (0.87)			-0.01 (-0.02, 0.01)	-0.67 (0.50)			0.00 (-0.02, 0.01)	-0.37 (0.71)		
Green space	0.00 (0.00, 0.00)	0.47 (0.64)			0.00 (0.00, 0.00)	0.72 (0.47)			0.00 (0.00, 0.00)	0.73 (0.46)		
Model 2 statistics			0.01	F(2, 4861) = 0.15 *p* = 0.86			0.01	F(2, 4859) = 0.28 *p* = 0.76			0.02	F(2, 2526) = 0.30 *p* = 0.74
Model 3: Urban-rural classification + green space + scenic level												
Urban-rural classification	0.00 (-0.02, 0.01)	-0.29 (0.77)			-0.01 (-0.02, 0.01)	-1.04 (0.30)			-0.01 (-0.02, 0.01)	-0.76 (0.45)		
Green space	0.00 (0.00, 0.00)	0.35 (0.73)			0.00 (0.00, 0.00)	0.34 (0.73)			0.00 (0.00, 0.00)	0.41 (0.68)		
Scenic level	0.01 (-0.02, 0.04)	0.66 (0.51)			0.03 (0.00, 0.06)	2.12 (0.03)			0.03 (0.00, 0.07)	1.99 (0.05)		
Model 3 statistics			0.02	F(3, 4860) = 0.24 *p* = 0.87			0.10	F(3, 4858) = 1.68 *p* = 0.17			0.18	F(3, 2525) = 1.52 *p* = 0.21
Difference in Model 2 and Model 3			ΔR^2 = 0.01	F(1, 4860) = 0.44 *p* = 0.51			ΔR^2 = 0.09	F(1, 4858) = 4.49 *p* = 0.03			ΔR^2 = 0.16	F(1, 2525) = 3.97 *p* = 0.05

1 km	'there are lots of fun things to do where I live' (n = 2528)				'I wish I lived in a different house' (n = 2523)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.07 (-0.12, -0.01)	-2.41 (0.02)			0.10 (0.04, 0.16)	3.29 (0.001)		
Model 1 statistics			0.23	F(1, 2526) = 5.82 p = 0.02			0.43	F(1, 2521) = 10.82 p = 0.001
Model 2: Urban-rural classification + green space								
Urban-rural classification	-0.04 (-0.07, -0.01)	-2.58 (0.01)			0.00 (-0.04, 0.03)	-0.21 (0.83)		
Green space	0.00 (-0.01, 0.00)	-2.77 (0.01)			0.00 (0.00, 0.00)	0.85 (0.39)		
Model 2 statistics			2.14	F(2, 2525) = 27.60 $p = 1.40 \times 10^{12}$			0.04	F(2, 2520) = 0.56 p = 0.57
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	-0.04 (-0.07, -0.01)	-2.73 (0.01)			-0.02 (-0.05, 0.02)	-0.85 (0.40)		
Green space	0.00 (-0.01, 0.00)	-2.89 (0.004)			0.00 (0.00, 0.00)	0.34 (0.74)		
Scenic level	0.03 (-0.03, 0.09)	0.98 (0.33)			0.11 (0.04, 0.18)	3.24 (0.001)		
Model 3 statistics			2.18	F(3, 2524) = 18.72 $p = 5.23 \times 10^{12}$			0.46	F(3, 2519) = 3.88 p = 0.01
Difference in Model 2 and Model 3			$\Delta R^2 = 0.04$	F(1, 2524) = 0.97 p = 0.33			ΔR^2 = 0.42	F(1, 2519) = 10.53 p = 0.001

1 km	'I wish there were different people in my neighbourhood' (n = 2525)				'I like where I live' (n = 2524)			
	β (95% CIs)	t-value (*p*)	R^2	F statistic	β (95% CIs)	t-value (*p*)	R^2	F statistic
Model 1: Scenic only								
Scenic	0.00 (-0.06, 0.05)	-0.14 (0.89)			0.07 (0.02, 0.11)	2.93 (0.003)		
Model 1 statistics			0.00	F(1, 2523) = 0.02 *p* = 0.89			0.34	F(1, 2522) = 8.59 *p* = 0.003
Model 2: Urban-rural classification + green space								
Urban-rural classification	-0.05 (-0.08, -0.02)	-2.95 (0.003)			-0.02 (-0.04, 0.01)	-1.27 (0.20)		
Green space	0.00 (0.00, 0.00)	-0.62 (0.54)			0.00 (0.00, 0.00)	0.66 (0.51)		
Model 2 statistics			1.02	F(2, 2522) = 13.03 *p* = 2.34 x10^6			0.07	F(2, 2521) = 0.90 *p* = 0.41
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	-0.06 (-0.09, -0.02)	-3.36 (0.0008)			-0.03 (-0.05, 0.00)	-1.99 (0.05)		
Green space	0.00 (0.00, 0.00)	-0.98 (0.33)			0.00 (0.00, 0.00)	0.07 (0.94)		
Scenic level	0.08 (0.01, 0.14)	2.35 (0.02)			0.09 (0.04, 0.14)	3.73 (0.0001)		
Model 3 statistics			1.24	F(3, 2521) = 10.54 *p* = 6.87 x10^7			0.62	F(3, 2520) = 5.23 *p* = 0.001
Difference in Model 2 and Model 3			ΔR^2 = 0.22	F(1, 2521) = 5.52 *p* = 0.02			ΔR^2 = 0.55	F(1, 2520) = 13.89 *p* = 0.0002

2 km	Subjective Happiness (n = 4930)				Life Satisfaction (n = 4928)				Subjective Health (n = 2553)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only												
Scenic	0.01 (-0.02, 0.05)	0.62 (0.54)			0.03 (0.00, 0.07)	1.77 (0.08)			0.03 (-0.01, 0.07)	1.51 (0.13)		
Model 1 statistics			0.01	F(1, 4862) = 0.38 p = 0.54			0.06	F(1, 4860) = 3.14 p = 0.08			0.09	F(1, 2527) = 2.29 p = 0.13
Model 2: Urban-rural classification + green space												
Urban-rural classification	-0.01 (-0.03, 0.01)	-1.39 (0.16)			0.00 (0.00, 0.00)	-2.02 (0.04)			-0.01 (-0.04, 0.01)	-1.29 (0.20)		
Green space	0.00 (0.00, 0.00)	1.94 (0.05)			0.00 (0.00, 0.00)	2.42 (0.02)			0.00 (0.00, 0.00)	1.51 (0.13)		
Model 2 statistics			0.08	F(2, 4861) = 2 p = 0.14			0.12	F(2, 4859) = 2.94 p = 0.05			0.09	F(2, 2526) = 1.14 p = 0.32
Model 3: Urban-rural classification + green space + scenic level												
Urban-rural classification	-0.01 (-0.03, 0.01)	-1.35 (0.18)			-0.02 (-0.04, 0.00)	-2.27 (0.02)			-0.02 (-0.04, 0.00)	-1.55 (0.12)		
Green space	0.00 (0.00, 0.00)	1.90 (0.06)			0.00 (0.00, 0.00)	1.87 (0.06)			0.00 (0.00, 0.00)	1.00 (0.32)		
Scenic level	0.00 (-0.05, 0.04)	-0.14 (0.89)			0.04 (-0.01, 0.09)	1.58 (0.11)			0.04 (-0.01, 0.10)	1.57 (0.12)		
Model 3 statistics			0.08	F(3, 4860) = 1.34 p = 0.26			0.17	F(3, 4858) = 2.79 p = 0.04			0.19	F(3, 2525) = 1.58 p = 0.19
Difference in Model 2 and Model 3			ΔR^2 = 0.00	F(1, 4860) = 0.02 p = 0.89			ΔR^2 = 0.05	F(1, 4858) = 2.51 p = 0.11			ΔR^2 = 0.10	F(1, 2525) = 2.46 p = 0.12

2 km	‘there are lots of fun things to do where I live’ (n = 2528)				‘I wish I lived in a different house’ (n = 2523)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.11 (-0.18, -0.04)	-2.93 (0.00)			0.12 (0.04, 0.21)	3 (0.002)		
Model 1 statistics			0.34	F(1, 2526) = 8.56 p = 0.003			0.35	F(1, 2521) = 8.97 p = 0.002
Model 2: Urban-rural classification + green space								
Urban-rural classification	-0.02 (-0.06, 0.02)	-0.91 (0.36)			-0.01 (-0.05, 0.04)	-0.35 (0.72)		
Green space	-0.01 (-0.01, 0.00)	-3.48 (0.001)			0.00 (0.00, 0.01)	0.87 (0.38)		
Model 2 statistics			2.43	F(2, 2525) = 31.51 $p = 3.04 \times 10^{14}$			0.05	F(2, 2520) = 0.62 p = 0.54
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	-0.03 (-0.07, 0.01)	-1.43 (0.15)			-0.02 (-0.06, 0.02)	-0.92 (0.36)		
Green space	-0.01 (-0.01, 0.00)	-4.18 (2.97×10^{5})			0.00 (0.00, 0.00)	-0.07 (0.95)		
Scenic level	0.14 (0.05, 0.24)	2.94 (0.003)			0.17 (0.06, 0.28)	3.13 (0.002)		
Model 3 statistics			2.77	F(3, 2524) = 23.95 $p = 2.81 \times 10^{15}$			0.44	F(3, 2519) = 3.69 p = 0.01
Difference in Model 2 and Model 3			ΔR^2 = 0.33	F(1, 2524) = 8.63 p = 0.003			ΔR^2 = 0.39	F(1, 2519) = 9.81 p = 0.002

2 km	‘I wish there were different people in my neighbourhood’ (n = 2525)				‘I like where I live’ (n = 2524)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.06 (-0.13, 0.02)	-1.39 (0.16)			0.10 (0.04, 0.16)	3.30 (0.001)		
Model 1 statistics			0.08	$F(1, 2523) = 1.94$ $p = 0.16$			0.43	$F(1, 2522) = 10.89$ $p = 0.001$
Model 2: Urban-rural classification + green space								
Urban-rural classification	-0.03 (-0.07, 0.01)	-1.41 (0.16)			-0.01 (-0.05, 0.02)	-0.89 (0.38)		
Green space	0.00 (-0.01, 0.00)	-1.12 (0.26)			0.00 (0.00, 0.00)	0.53 (0.60)		
Model 2 statistics			0.80	$F(2, 2522) = 10.18$ $p = 3.93 \times 10^{5}$			0.04	$F(2, 2521) = 0.48$ $p = 0.62$
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	-0.04 (-0.08, 0.00)	-1.76 (0.08)			-0.03 (-0.06, 0.00)	-1.77 (0.08)		
Green space	0.00 (-0.01, 0.00)	-1.66 (0.10)			0.00 (0.00, 0.00)	-0.90 (0.37)		
Scenic level	0.11 (0.00, 0.21)	2.05 (0.04)			0.20 (0.12, 0.28)	4.89 (1.07×10^{6})		
Model 3 statistics			0.97	$F(3, 2521) = 8.20$ $p = 1.99 \times 10^{5}$			0.98	$F(3, 2520) = 8.29$ $p = 1.74 \times 10^{5}$
Difference in Model 2 and Model 3			$\Delta R^2 = 0.16$	$F(1, 2521) = 4.19$ $p = 0.04$			$\Delta R^2 = 0.94$	$F(1, 2520) = 23.91$ $p = 1.07 \times 10^{6}$

3 km	Subjective Happiness (n = 4930)				Life Satisfaction (n = 4928)				Subjective Health (n = 2553)			
	β (95% CIs)	t-value (*p*)	R^2	F statistic	β (95% CIs)	t-value (*p*)	R^2	F statistic	β (95% CIs)	t-value (*p*)	R^2	F statistic
Model 1: Scenic only												
Scenic	0.02 (-0.02, 0.05)	0.82 (0.41)			0.04 (0.00, 0.08)	1.76 (0.08)			0.04 (-0.01, 0.08)	1.69 (0.09)		
Model 1 statistics			0.01	F(1, 4862) = 0.67 *p* = 0.41			0.06	F(1, 4860) = 3.11 *p* = 0.08			0.11	F(1, 2527) = 2.87 *p* = 0.09
Model 2: Urban-rural classification + green space												
Urban-rural classification	-0.01 (-0.04, 0.01)	-1.35 (0.18)			-0.02 (-0.05, 0.00)	-2.07 (0.04)			-0.02 (-0.04, 0.01)	-1.21 (0.22)		
Green space	0.00 (0.00, 0.00)	1.99 (0.05)			0.00 (0.00, 0.00)	2.47 (0.01)			0.00 (0.00, 0.00)	1.48 (0.14)		
Model 2 statistics			0.10	F(2, 4861) = 2.34 *p* = 0.10			0.13	F(2, 4859) = 3.08 *p* = 0.05			0.09	F(2, 2526) = 1.11 *p* = 0.33
Model 3: Urban-rural classification + green space + scenic level												
Urban-rural classification	-0.01 (-0.04, 0.01)	-1.26 (0.21)			-0.03 (-0.05, 0.00)	-2.35 (0.02)			-0.02 (-0.04, 0.01)	-1.56 (0.12)		
Green space	0.00 (0.00, 0.00)	1.99 (0.05)			0.00 (0.00, 0.00)	1.88 (0.06)			0.00 (0.00, 0.00)	0.81 (0.42)		
Scenic level	-0.01 (-0.07, 0.05)	-0.30 (0.76)			0.05 (-0.01, 0.11)	1.58 (0.11)			0.06 (0.00, 0.13)	1.84 (0.07)		
Model 3 statistics			0.10	F(3, 4860) = 1.59 *p* = 0.19			0.18	F(3, 4858) = 2.89 *p* = 0.03			0.22	F(3, 2525) = 1.87 *p* = 0.13
Difference in Model 2 and Model 3			ΔR^2 = 0.00	F(1, 4860) = 0.09 *p* = 0.76			0.05	F(1, 4858) = 2.51 *p* = 0.11			ΔR^2 = 0.13	F(1, 2525) = 3.40 *p* = 0.07

3 km	**‘there are lots of fun things to do where I live’** (n = 2528)				**‘I wish I lived in a different house’** (n = 2523)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.14 (-0.22, -0.06)	-3.30 (0.001)			0.11 (0.02, 0.21)	2.45 (0.01)		
Model 1 statistics			0.43	F(1, 2526) = 10.91 p = 0.001			0.24	F(1, 2521) = 6.00 p = 0.01
Model 2: Urban-rural classification + green space								
Urban-rural classification	-0.01 (-0.05, 0.03)	-0.42 (0.67)			0.00 (-0.05, 0.05)	-0.07 (0.95)		
Green space	-0.01 (-0.01, 0.00)	-3.39 (0.001)			0.00 (0.00, 0.01)	0.41 (0.68)		
Model 2 statistics			2.42	F(2, 2525) = 31.33 $p = 3.62 \times 10^{14}$			0.02	F(2, 2520) = 0.28 p = 0.76
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	-0.03 (-0.07, 0.02)	-1.17 (0.24)			-0.02 (-0.07, 0.03)	-0.65 (0.52)		
Green space	-0.01 (-0.02, -0.01)	-4.41 (1.08×10^{5})			0.00 (-0.01, 0.00)	-0.53 (0.60)		
Scenic level	0.23 (0.11, 0.35)	3.74 (0.0002)			0.20 (0.06, 0.34)	2.87 (0.004)		
Model 3 statistics			2.96	F(3, 2524) = 25.65 $p = 2.43 \times 10^{16}$			0.35	F(3, 2519) = 2.93 p = 0.03
Difference in Model 2 and Model 3			ΔR^2 = 0.54	F(1, 2524) = 13.96 p = 0.0001			ΔR^2 = 0.33	F(1, 2519) = 8.23 p = 0.004

3 km	‘I wish there were different people in my neighbourhood’ (n = 2525)				‘I like where I live’ (n = 2524)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.09 (-0.18, 0.00)	-1.99 (0.05)			0.09 (0.02, 0.16)	2.53 (0.01)		
Model 1 statistics			0.16	F(1, 2523) = 3.96 p = 0.05			0.25	F(1, 2522) = 6.41 p = 0.01
Model 2: Urban-rural classification + green space								
Urban-rural classification	-0.03 (-0.08, 0.02)	-1.26 (0.21)			-0.01 (-0.05, 0.02)	-0.72 (0.47)		
Green space	0.00 (-0.01, 0.00)	-0.71 (0.48)			0.00 (0.00, 0.00)	0.40 (0.69)		
Model 2 statistics			0.64	F(2, 2522) = 8.12 p = 0.0003			0.03	F(2, 2521) = 0.38 p = 0.68
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	-0.04 (-0.09, 0.01)	-1.53 (0.13)			-0.03 (-0.07, 0.01)	-1.62 (0.10)		
Green space	0.00 (-0.01, 0.00)	-1.14 (0.26)			0.00 (-0.01, 0.00)	-1.05 (0.29)		
Scenic level	0.10 (-0.03, 0.23)	1.46 (0.14)			0.23 (0.13, 0.34)	4.49 (7.37 $\times10^{6}$)		
Model 3 statistics			0.72	F(3, 2521) = 6.13 p = 0.0003			0.82	F(3, 2520) = 6.98 p = 0.0001
Difference in Model 2 and Model 3			ΔR^2 = 0.08	F(1, 2521) = 2.13 p = 0.14			ΔR^2 = 0.79	F(1, 2520) = 20.18 p = 7.37 $\times10^{6}$

4 km	Subjective Happiness (n = 4930)				Life Satisfaction (n = 4928)				Subjective Health (n = 2553)			
	β (95% CIs)	t-value (*p*)	R^2	F statistic	β (95% CIs)	t-value (*p*)	R^2	F statistic	β (95% CIs)	t-value (*p*)	R^2	F statistic
Model 1: Scenic only												
Scenic	0.02 (-0.02, 0.06)	0.97 (0.33)			0.04 (0.00, 0.08)	1.79 (0.07)			0.03 (-0.01, 0.08)	1.43 (0.15)		
Model 1 statistics			0.02	F(1, 4862) = 0.95 *p* = 0.33			0.07	F(1, 4860) = 3.19 *p* = 0.07			0.08	F(1, 2527) = 2.03 *p* = 0.15
Model 2: Urban-rural classification + green space												
Urban-rural classification	-0.02 (-0.04, 0.01)	-1.41 (0.16)			-0.02 (-0.05, 0.00)	-1.92 (0.05)			-0.02 (-0.05, 0.01)	-1.40 (0.16)		
Green space	0.00 (0.00, 0.01)	2.02 (0.04)			0.00 (0.00, 0.01)	2.26 (0.02)			0.00 (0.00, 0.01)	1.61 (0.11)		
Model 2 statistics			0.10	F(2, 4861) = 2.52 *p* = 0.08			0.11	F(2, 4859) = 2.59 *p* = 0.08			0.10	F(2, 2526) = 1.30 *p* = 0.27
Model 3: Urban-rural classification + green space + scenic level												
Urban-rural classification	-0.02 (-0.04, 0.01)	-1.32 (0.19)			-0.03 (-0.05, 0.00)	-2.30 (0.02)			-0.02 (-0.05, 0.00)	-1.72 (0.09)		
Green space	0.00 (0.00, 0.01)	2.00 (0.05)			0.00 (0.00, 0.00)	1.66 (0.10)			0.00 (0.00, 0.00)	1.04 (0.30)		
Scenic level	-0.01 (-0.07, 0.06)	-0.21 (0.83)			0.06 (0.00, 0.13)	1.83 (0.07)			0.06 (-0.01, 0.14)	1.61 (0.11)		
Model 3 statistics			0.10	F(3, 4860) = 1.70 *p* = 0.17			0.18	F(3, 4858) = 2.85 *p* = 0.04			0.21	F(3, 2525) = 1.73 *p* = 0.16
Difference in Model 2 and Model 3			ΔR^2 = 0.00	F(1, 4860) = 0.04 *p* = 0.83			ΔR^2 = 0.07	F(1, 4858) = 3.36 *p* = 0.07			ΔR^2 = 0.10	F(1, 2525) = 2.60 *p* = 0.11

4 km	‘there are lots of fun things to do where I live’ (n = 2528)				‘I wish I lived in a different house’ (n = 2523)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.15 (-0.23, -0.06)	-3.37 (0.001)			0.10 (0.00, 0.20)	2.03 (0.04)		
Model 1 statistics			0.45	F(1, 2526) = 11.38 p = 0.001			0.16	F(1, 2521) = 4.11 p = 0.04
Model 2: Urban-rural classification + green space								
Urban-rural classification	-0.01 (-0.06, 0.04)	-0.24 (0.81)			-0.01 (-0.07, 0.04)	-0.48 (0.63)		
Green space	-0.01 (-0.01, 0.00)	-2.99 (0.002)			0.00 (0.00, 0.01)	0.71 (0.48)		
Model 2 statistics			2.16	F(2, 2525) = 27.87 p = 0.001			0.03	F(2, 2520) = 0.32 p = 0.73
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	-0.03 (-0.08, 0.02)	-1.08 (0.28)			-0.03 (-0.09, 0.03)	-1.05 (0.30)		
Green space	-0.01 (-0.02, -0.01)	-4.02 (6.09×10^5)			0.00 (-0.01, 0.01)	-0.12 (0.91)		
Scenic level	0.26 (0.13, 0.40)	3.79 (0.0001)			0.20 (0.05, 0.36)	2.58 (0.01)		
Model 3 statistics			2.71	F(3, 2524) = 23.47 $p = 5.60 \times 10^{15}$			0.29	F(3, 2519) = 2.43 p = 0.06
Difference in Model 2 and Model 3			ΔR^2 = 0.55	F(1, 2524) = 14.37 p = 0.0001			ΔR^2 = 0.26	F(1, 2519) = 6.66 p = 0.01

4 km	'I wish there were different people in my neighbourhood' (n = 2525)				'I like where I live' (n = 2524)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.09 (-0.18, 0.00)	-1.86 (0.06)			0.08 (0.00, 0.15)	2.09 (0.04)		
Model 1 statistics			0.14	F(1, 2523) = 3.45 p = 0.06			0.17	F(1, 2522) = 4.38 p = 0.04
Model 2: Urban-rural classification + green space								
Urban-rural classification	-0.03 (-0.09, 0.02)	-1.19 (0.23)			-0.01 (-0.05, 0.03)	-0.55 (0.58)		
Green space	0.00 (-0.01, 0.00)	-0.39 (0.69)			0.00 (0.00, 0.00)	0.28 (0.78)		
Model 2 statistics			0.52	F(2, 2522) = 6.55 p = 0.001			0.02	F(2, 2521) = 0.27 p = 0.76
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	-0.04 (-0.10, 0.01)	-1.49 (0.14)			-0.03 (-0.07, 0.01)	-1.45 (0.15)		
Green space	0.00 (-0.01, 0.00)	-0.83 (0.40)			0.00 (-0.01, 0.00)	-0.98 (0.32)		
Scenic level	0.11 (-0.04, 0.26)	1.50 (0.13)			0.24 (0.13, 0.36)	4.09 (4.44 x10^5)		
Model 3 statistics			0.60	F(3, 2521) = 5.11 p = 0.001			0.68	F(3, 2520) = 5.76 p = 0.0006
Difference in Model 2 and Model 3			ΔR^2 = 0.09	F(1, 2521) = 2.24 p = 0.13			ΔR^2 = 0.66	F(1, 2520) = 16.73 p = 4.44 x10^5

5 km	Subjective Happiness (n = 4864)				Life Satisfaction (n = 4862)				Subjective Health (n = 2529)			
	β (95% CIs)	t-value (*p*)	R^2	F statistic	β (95% CIs)	t-value (*p*)	R^2	F statistic	β (95% CIs)	t-value (*p*)	R^2	F statistic
Model 1: Scenic only												
Scenic	0.03 (-0.02, 0.07)	1.17 (0.24)			0.04 (0.00, 0.08)	1.81 (0.07)			0.03 (-0.02, 0.08)	1.18 (0.24)		
Model 1 statistics			0.03	F(1, 4862) = 1.36 *p* = 0.24			0.07	F(1, 4860) = 3.27 *p* = 0.07			0.05	F(1, 2527) = 1.38 *p* = 0.24
Model 2: Urban-rural classification + green space												
Urban-rural classification	-0.01 (-0.04, 0.01)	-1.07 (0.28)			-0.02 (-0.05, 0.00)	-1.71 (0.09)			-0.02 (-0.05, 0.01)	-1.17 (0.24)		
Green space	0.00 (0.00, 0.01)	1.61 (0.11)			0.00 (0.00, 0.01)	1.95 (0.05)			0.00 (0.00, 0.01)	1.31 (0.19)		
Model 2 statistics			0.07	F(2, 4861) = 1.82 *p* = 0.16			0.08	F(2, 4859) = 1.93 *p* = 0.15			0.07	F(2, 2526) = 0.87 *p* = 0.42
Model 3: Urban-rural classification + green space + scenic level												
Urban-rural classification	-0.01 (-0.04, 0.01)	-1.09 (0.28)			-0.03 (-0.06, 0.00)	-2.25 (0.02)			-0.02 (-0.05, 0.01)	-1.51 (0.13)		
Green space	0.00 (0.00, 0.01)	1.51 (0.13)			0.00 (0.00, 0.00)	1.36 (0.17)			0.00 (0.00, 0.00)	0.88 (0.38)		
Scenic level	0.01 (-0.06, 0.08)	0.21 (0.83)			0.08 (0.01, 0.15)	2.22 (0.03)			0.06 (-0.02, 0.14)	1.47 (0.14)		
Model 3 statistics			0.08	F(3, 4860) = 1.23 *p* = 0.30			0.18	F(3, 4858) = 2.93 *p* = 0.03			0.15	F(3, 2525) = 1.3 *p* = 0.27
Difference in Model 2 and Model 3			ΔR^2 = 0.00	F(1, 4860) = 0.05 *p* = 0.83			ΔR^2 = 0.10	F(1, 4858) = 4.95 *p* = 0.03			ΔR^2 = 0.09	F(1, 2525) = 2.17 *p* = 0.14

5 km	'there are lots of fun things to do where I live' (n = 2528)				'I wish I lived in a different house' (n = 2523)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.16 (-0.25, -0.07)	-3.51 (0.00)			0.10 (0.00, 0.20)	1.93 (0.05)		
Model 1 statistics			0.48	$F(1, 2526) = 12.31$ $p = 0.0005$			0.15	$F(1, 2521) = 3.73$ $p = 0.05$
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.01 (-0.04, 0.06)	0.38 (0.71)			-0.02 (-0.08, 0.04)	-0.57 (0.57)		
Green space	-0.01 (-0.02, 0.00)	-3.15 (0.00)			0.00 (0.00, 0.01)	0.67 (0.50)		
Model 2 statistics			1.94	$F(2, 2525) = 25.01$ $p = 1.76\text{x}10^{11}$			0.02	$F(2, 2520) = 0.24$ $p = 0.79$
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	-0.01 (-0.07, 0.04)	-0.46 (0.64)			-0.04 (-0.10, 0.02)	-1.29 (0.20)		
Green space	-0.01 (-0.02, -0.01)	-3.90 (0.00)			0.00 (-0.01, 0.01)	-0.10 (0.92)		
Scenic level	0.24 (0.10, 0.39)	3.22 (0.00)			0.25 (0.08, 0.41)	2.87 (0.004)		
Model 3 statistics			2.34	$F(3, 2524) = 20.18$ $p = 6.35\text{ x}10^{13}$			0.34	$F(3, 2519) = 2.89$ $p = 0.03$
Difference in Model 2 and Model 3			$\Delta R^2 = 0.40$	$F(1, 2524) = 10.34$ $p = 0.001$			$\Delta R^2 = 0.32$	$F(1, 2519) = 8.21$ $p = 0.004$

5 km	'I wish there were different people in my neighbourhood' (n = 2525)				'I like where I live' (n = 2524)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.11 (-0.20, -0.01)	-2.15 (0.03)			0.07 (-0.01, 0.15)	1.82 (0.07)		
Model 1 statistics			0.18	F(1, 2523) = 4.61 p = 0.03			0.13	F(1, 2522) = 3.31 p = 0.07
Model 2: Urban-rural classification + green space								
Urban-rural classification	-0.03 (-0.09, 0.03)	-1.00 (0.32)			0.00 (-0.05, 0.04)	-0.15 (0.88)		
Green space	0.00 (-0.01, 0.01)	-0.34 (0.74)			0.00 (-0.01, 0.00)	-0.08 (0.94)		
Model 2 statistics			0.43	F(2, 2522) = 5.50 p = 0.004			0.01	F(2, 2521) = 0.16 p = 0.85
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	-0.04 (-0.10, 0.02)	-1.18 (0.24)			-0.03 (-0.07, 0.02)	-1.11 (0.27)		
Green space	0.00 (-0.01, 0.00)	-0.54 (0.59)			0.00 (-0.01, 0.00)	-1.07 (0.28)		
Scenic level	0.07 (-0.09, 0.23)	0.81 (0.42)			0.24 (0.12, 0.37)	3.78 (0.002)		
Model 3 statistics			0.46	F(3, 2521) = 3.89 p = 0.01			0.57	F(3, 2520) = 4.86 p = 0.002
Difference in Model 2 and Model 3			ΔR^2 = 0.03	F(1, 2521) = 0.65 p = 0.42			ΔR^2 = 0.56	F(1, 2520) = 14.26 p = 0.0002

6 km	Subjective Happiness (n = 4930)				Life Satisfaction (n = 4928)				Subjective Health (n = 2553)			
	β (95% CIs)	t-value (*p*)	R^2	F statistic	β (95% CIs)	t-value (*p*)	R^2	F statistic	β (95% CIs)	t-value (*p*)	R^2	F statistic
Model 1: Scenic only												
Scenic	0.03 (-0.02, 0.07)	1.16 (0.25)			0.03 (-0.01, 0.08)	1.46 (0.14)			0.02 (-0.03, 0.07)	0.76 (0.44)		
Model 1 statistics			0.03	F(1, 4862) = 1.35 *p* = 0.25			0.04	F(1, 4860) = 2.13 *p* = 0.14			0.02	F(1, 2527) = 0.58 *p* = 0.44
Model 2: Urban-rural classification + green space												
Urban-rural classification	-0.01 (-0.04, 0.02)	-0.69 (0.49)			-0.02 (-0.05, 0.01)	-1.48 (0.14)			-0.02 (-0.05, 0.02)	-1.04 (0.30)		
Green space	0.00 (0.00, 0.00)	1.18 (0.24)			0.00 (0.00, 0.01)	1.60 (0.11)			0.00 (0.00, 0.01)	1.12 (0.26)		
Model 2 statistics			0.05	F(2, 4861) = 1.26 *p* = 0.28			0.05	F(2, 4859) = 1.28 *p* = 0.28			0.05	F(2, 2526) = 0.63 *p* = 0.53
Model 3: Urban-rural classification + green space + scenic level												
Urban-rural classification	-0.01 (-0.04, 0.02)	-0.75 (0.45)			-0.03 (-0.06, 0.00)	-2.04 (0.04)			-0.02 (-0.06, 0.01)	-1.28 (0.20)		
Green space	0.00 (0.00, 0.00)	1.09 (0.27)			0.00 (0.00, 0.00)	1.12 (0.26)			0.00 (0.00, 0.01)	0.85 (0.39)		
Scenic level	0.01 (-0.06, 0.08)	0.29 (0.78)			0.08 (0.01, 0.16)	2.12 (0.03)			0.05 (-0.04, 0.13)	1.03 (0.30)		
Model 3 statistics			0.05	F(3, 4860) = 0.86 *p* = 0.46			0.15	F(3, 4858) = 2.35 *p* = 0.07			0.09	F(3, 2525) = 0.77 *p* = 0.51
Difference in Model 2 and Model 3			$\Delta R^2 = 0$	F(1, 4860) = 0.08 *p* = 0.78			$\Delta R^2 = 0.09$	F(1, 4858) = 4.49 *p* = 0.03			$\Delta R^2 = 0.04$	F(1, 2525) = 1.06 *p* = 0.30

6 km	'there are lots of fun things to do where I live' (n = 2528)				'I wish I lived in a different house' (n = 2523)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.18 (-0.27, -0.09)	-3.81 (0.0001)			0.08 (-0.02, 0.19)	1.59 (0.11)		
Model 1 statistics			0.57	F(1, 2526) = 14.5 p = 0.0001			0.10	F(1, 2521) = 2.54 p = 0.11
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.02 (-0.04, 0.08)	0.65 (0.51)			-0.03 (-0.1, 0.04)	-0.90 (0.37)		
Green space	-0.01 (-0.02, 0.00)	-3.12 (0.002)			0.00 (0.00, 0.01)	0.93 (0.35)		
Model 2 statistics			1.77	F(2, 2525) = 22.7 $p = 1.69 \times 10^{10}$			0.03	F(2, 2520) = 0.44 p = 0.65
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	0.00 (-0.06, 0.06)	0.00 (1.00)			-0.05 (-0.12, 0.01)	-1.57 (0.12)		
Green space	-0.01 (-0.02, -0.01)	-3.57 (0.0003)			0.00 (-0.01, 0.01)	0.29 (0.77)		
Scenic level	0.18 (0.03, 0.34)	2.30 (0.02)			0.24 (0.06, 0.41)	2.62 (0.01)		
Model 3 statistics			1.97	F(3, 2524) = 16.92 $p = 7.01 \times 10^{11}$			0.31	F(3, 2519) = 2.57 p = 0.05
Difference in Model 2 and Model 3			ΔR^2 = 0.21	F(1, 2524) = 5.28 p = 0.02			ΔR^2 = 0.27	F(1, 2519) = 6.85 p = 0.01

6 km	'I wish there were different people in my neighbourhood' (n = 2525)				'I like where I live' (n = 2524)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.11 (-0.21, -0.01)	-2.18 (0.03)			0.07 (-0.01, 0.15)	1.83 (0.07)		
Model 1 statistics			0.19	F(1, 2523) = 4.77 p = 0.03			0.13	F(1, 2522) = 3.33 p = 0.07
Model 2: Urban-rural classification + green space								
Urban-rural classification	-0.02 (-0.08, 0.05)	-0.54 (0.59)			-0.01 (-0.06, 0.04)	-0.36 (0.72)		
Green space	0.00 (-0.01, 0.00)	-0.62 (0.54)			0.00 (0.00, 0.01)	0.22 (0.83)		
Model 2 statistics			0.37	F(2, 2522) = 4.69 p = 0.01			0.01	F(2, 2521) = 0.11 p = 0.90
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	-0.02 (-0.09, 0.04)	-0.66 (0.51)			-0.03 (-0.09, 0.02)	-1.31 (0.19)		
Green space	0.00 (-0.01, 0.00)	-0.72 (0.47)			0.00 (-0.01, 0.00)	-0.63 (0.53)		
Scenic level	0.04 (-0.13, 0.21)	0.49 (0.63)			0.24 (0.11, 0.38)	3.60 (0.0003)		
Model 3 statistics			0.38	F(3, 2521) = 3.2 p = 0.02			0.52	F(3, 2520) = 4.40 p = 0.004
Difference in Model 2 and Model 3			ΔR^2 = 0.01	F(1, 2521) = 0.24 p = 0.63			ΔR^2 = 0.51	F(1, 2520) = 12.98 p = 0.0003

7 km	Subjective Happiness (n = 4930)				Life Satisfaction (n = 4928)				Subjective Health (n = 2553)			
	β (95% CIs)	t-value (*p*)	R^2	F statistic	β (95% CIs)	t-value (*p*)	R^2	F statistic	β (95% CIs)	t-value (*p*)	R^2	F statistic
Model 1: Scenic only												
Scenic	0.02 (-0.02, 0.07)	1.02 (0.31)			0.02 (-0.02, 0.07)	0.91 (0.36)			0.01 (-0.04, 0.06)	0.31 (0.75)		
Model 1 statistics			0.02	F(1, 4862) = 1.04 *p* = 0.31			0.02	F(1, 4860) = 0.82 *p* = 0.36			0.00	F(1, 2527) = 0.10 *p* = 0.75
Model 2: Urban-rural classification + green space												
Urban-rural classification	-0.01 (-0.04, 0.02)	-0.78 (0.43)			-0.02 (-0.05, 0.01)	-1.55 (0.12)			-0.01 (-0.05, 0.02)	-0.71 (0.48)		
Green space	0.00 (0.00, 0.01)	1.21 (0.23)			0.00 (0.00, 0.01)	1.54 (0.12)			0.00 (0.00, 0.01)	0.74 (0.46)		
Model 2 statistics			0.05	F(2, 4861) = 1.19 *p* = 0.30			0.05	F(2, 4859) = 1.23 *p* = 0.29			0.02	F(2, 2526) = 0.28 *p* = 0.76
Model 3: Urban-rural classification + green space + scenic level												
Urban-rural classification	-0.01 (-0.04, 0.02)	-0.80 (0.42)			-0.03 (-0.06, 0.00)	-1.99 (0.05)			-0.01 (-0.05, 0.02)	-0.80 (0.42)		
Green space	0.00 (0.00, 0.01)	1.15 (0.25)			0.00 (0.00, 0.01)	1.20 (0.23)			0.00 (0.00, 0.01)	0.64 (0.52)		
Scenic level	0.01 (-0.07, 0.09)	0.19 (0.85)			0.07 (-0.01, 0.15)	1.69 (0.09)			0.02 (-0.07, 0.11)	0.44 (0.66)		
Model 3 statistics			0.05	F(3, 4860) = 0.81 *p* = 0.49			0.11	F(3, 4858) = 1.77 *p* = 0.15			0.03	F(3, 2525) = 0.25 *p* = 0.86
Difference in Model 2 and Model 3			ΔR^2 = 0.00	F(1, 4860) = 0.04 *p* = 0.85			ΔR^2 = 0.06	F(1, 4858) = 2.85 *p* = 0.09			ΔR^2 = 0.01	F(1, 2525) = 0.19 *p* = 0.66

7 km	**‘there are lots of fun things to do where I live’** (n = 2528)				**‘I wish I lived in a different house’** (n = 2523)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.19 (-0.29, -0.10)	-3.94 (8.38×10^{5})			0.07 (-0.04, 0.18)	1.29 (0.20)		
Model 1 statistics			0.61	$F(1, 2526) = 15.52$ $p = 8.38 \times 10^{5}$			0.07	$F(1, 2521) = 1.66$ $p = 0.20$
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.03 (-0.03, 0.09)	1.02 (0.31)			-0.03 (-0.10, 0.04)	-0.83 (0.41)		
Green space	-0.01 (-0.02, 0.00)	-3.25 (0.001)			0.00 (0.00, 0.01)	0.79 (0.43)		
Model 2 statistics			1.69	$F(2, 2525) = 21.65$ $p = 4.74 \times 10^{10}$			0.03	$F(2, 2520) = 0.34$ $p = 0.71$
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	0.02 (-0.05, 0.08)	0.47 (0.64)			-0.06 (-0.13, 0.02)	-1.48 (0.14)		
Green space	-0.01 (-0.02, -0.01)	-3.55 (0.0003)			0.00 (-0.01, 0.01)	0.28 (0.78)		
Scenic level	0.15 (-0.01, 0.31)	1.79 (0.07)			0.23 (0.04, 0.41)	2.41 (0.02)		
Model 3 statistics			1.81	$F(3, 2524) = 15.51$ $p = 5.35 \times 10^{10}$			0.26	$F(3, 2519) = 2.17$ $p = 0.09$
Difference in Model 2 and Model 3			$\Delta R^2 = 0.12$	$F(1, 2524) = 3.19$ $p = 0.07$			$\Delta R^2 =$ 0.23	$F(1, 2519) = 5.83$ $p = 0.02$

7 km	'I wish there were different people in my neighbourhood' (n = 2525)				'I like where I live' (n = 2524)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.10 (-0.21, 0.00)	-1.99 (0.05)			0.07 (-0.01, 0.15)	1.65 (0.10)		
Model 1 statistics			0.16	F(1, 2523) = 3.95 *p* = 0.05			0.11	F(1, 2522) = 2.73 *p* = 0.10
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.00 (-0.07, 0.07)	-0.04 (0.97)			-0.01 (-0.06, 0.04)	-0.31 (0.75)		
Green space	0.00 (-0.01, 0.00)	-1.01 (0.31)			0.00 (-0.01, 0.01)	0.22 (0.83)		
Model 2 statistics			0.35	F(2, 2522) = 4.43 *p* = 0.01			0.01	F(2, 2521) = 0.07 *p* = 0.93
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	-0.01 (-0.08, 0.06)	-0.23 (0.82)			-0.03 (-0.09, 0.02)	-1.22 (0.22)		
Green space	0.00 (-0.01, 0.00)	-1.13 (0.26)			0.00 (-0.01, 0.00)	-0.45 (0.66)		
Scenic level	0.06 (-0.12, 0.24)	0.67 (0.50)			0.23 (0.09, 0.37)	3.23 (0.001)		
Model 3 statistics			0.37	F(3, 2521) = 3.10 *p* = 0.03			0.42	F(3, 2520) = 3.53 *p* = 0.01
Difference in Model 2 and Model 3			ΔR^2 = 0.02	F(1, 2521) = 0.45 *p* = 0.50			ΔR^2 = 0.41	F(1, 2520) = 10.44 *p* = 0.001

8 km	Subjective Happiness (n = 4930)				Life Satisfaction (n = 4928)				Subjective Health (n = 2553)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only												
Scenic	0.02 (-0.02, 0.07)	0.95 (0.34)			0.01 (-0.03, 0.06)	0.61 (0.54)			0.00 (-0.05, 0.06)	0.07 (0.95)		
Model 1 statistics			0.02	F(1, 4862) = 0.90 p = 0.34			0.01	F(1, 4860) = 0.37 p = 0.54			0.00	F(1, 2527) = 0.00 p = 0.95
Model 2: Urban-rural classification + green space												
Urban-rural classification	-0.01 (-0.05, 0.02)	-0.89 (0.37)			-0.03 (-0.06, 0.01)	-1.61 (0.11)			-0.01 (-0.05, 0.03)	-0.56 (0.57)		
Green space	0.00 (0.00, 0.01)	1.29 (0.20)			0.00 (0.00, 0.01)	1.54 (0.12)			0.00 (0.00, 0.01)	0.55 (0.58)		
Model 2 statistics			0.05	F(2, 4861) = 1.25 p = 0.29			0.05	F(2, 4859) = 1.30 p = 0.27			0.01	F(2, 2526) = 0.16 p = 0.85
Model 3: Urban-rural classification + green space + scenic level												
Urban-rural classification	-0.01 (-0.05, 0.02)	-0.89 (0.37)			-0.03 (-0.07, 0.00)	-2.00 (0.05)			-0.01 (-0.05, 0.03)	-0.60 (0.55)		
Green space	0.00 (0.00, 0.01)	1.25 (0.21)			0.00 (0.00, 0.01)	1.27 (0.20)			0.00 (0.00, 0.01)	0.50 (0.61)		
Scenic level	0.01 (-0.08, 0.09)	0.13 (0.90)			0.06 (-0.02, 0.15)	1.49 (0.14)			0.01 (-0.08, 0.10)	0.20 (0.84)		
Model 3 statistics			0.05	F(3, 4860) = 0.84 p = 0.47			0.10	F(3, 4858) = 1.61 p = 0.18			0.01	F(3, 2525) = 0.12 p = 0.95
Difference in Model 2 and Model 3			ΔR^2 = 0.00	F(1, 4860) = 0.02 p = 0.90			ΔR^2 = 0.05	F(1, 4858) = 2.23 p = 0.14			ΔR^2 = 0.00	F(1, 2525) = 0.04 p = 0.84

8 km	‘there are lots of fun things to do where I live’ (n = 2528)				‘I wish I lived in a different house’ (n = 2523)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.20 (-0.30, -0.10)	-4.02 (6.11 x10^5)			0.05 (-0.06, 0.16)	0.92 (0.36)		
Model 1 statistics			0.63	F(1, 2526) = 16.12 p = 6.11 x10^5			0.03	F(1, 2521) = 0.86 p = 0.36
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.05 (-0.02, 0.12)	1.48 (0.14)			-0.02 (-0.1, 0.05)	-0.62 (0.54)		
Green space	-0.01 (-0.02, -0.01)	-3.58 (0.0003)			0.00 (-0.01, 0.01)	0.55 (0.58)		
Model 2 statistics			1.70	F(2, 2525) = 21.79 p = 4.15 x10^{10}			0.02	F(2, 2520) = 0.20 p = 0.82
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	0.03 (-0.03, 0.1)	0.98 (0.33)			-0.05 (-0.12, 0.03)	-1.16 (0.25)		
Green space	-0.01 (-0.02, -0.01)	-3.79 (0.0002)			0.00 (-0.01, 0.01)	0.19 (0.85)		
Scenic level	0.13 (-0.04, 0.30)	1.45 (0.15)			0.19 (0.00, 0.38)	1.94 (0.05)		
Model 3 statistics			1.78	F(3, 2524) = 15.24 p = 7.94 x10^{10}			0.16	F(3, 2519) = 1.38 p = 0.25
Difference in Model 2 and Model 3			ΔR^2 = 0.08	F(1, 2524) = 2.12 p = 0.15			ΔR^2 = 0.15	F(1, 2519) = 3.76 p = 0.05

8 km	'I wish there were different people in my neighbourhood' (n = 2525)				'I like where I live' (n = 2524)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.10 (-0.20, 0.01)	-1.81 (0.07)			0.07 (-0.02, 0.15)	1.56 (0.12)		
Model 1 statistics			0.13	F(1, 2523) = 3.28 p = 0.07			0.10	F(1, 2522) = 2.43 p = 0.12
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.01 (-0.06, 0.08)	0.18 (0.86)			-0.01 (-0.06, 0.05)	-0.23 (0.82)		
Green space	0.00 (-0.01, 0.00)	-1.13 (0.26)			0.00 (-0.01, 0.01)	0.19 (0.85)		
Model 2 statistics			0.32	F(2, 2522) = 4.01 p = 0.02			0.00	F(2, 2521) = 0.03 p = 0.97
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	0.00 (-0.08, 0.07)	-0.04 (0.97)			-0.03 (-0.09, 0.03)	-1.07 (0.29)		
Green space	-0.01 (-0.01, 0.00)	-1.24 (0.22)			0.00 (-0.01, 0.01)	-0.34 (0.74)		
Scenic level	0.07 (-0.12, 0.25)	0.72 (0.47)			0.21 (0.07, 0.35)	2.89 (0.004)		
Model 3 statistics			0.34	F(3, 2521) = 2.85 p = 0.04			0.33	F(3, 2520) = 2.80 p = 0.04
Difference in Model 2 and Model 3			ΔR^2 = 0.02	F(1, 2521) = 0.52 p = 0.47			ΔR^2 = 0.33	F(1, 2520) = 8.35 p = 0.004

9 km	Subjective Happiness (n = 4930)				Life Satisfaction (n = 4928)				Subjective Health (n = 2553)			
	β (95% CIs)	t-value (*p*)	R^2	F statistic	β (95% CIs)	t-value (*p*)	R^2	F statistic	β (95% CIs)	t-value (*p*)	R^2	F statistic
Model 1: Scenic only												
Scenic	0.02 (-0.03, 0.07)	0.84 (0.40)			0.01 (-0.04, 0.06)	0.39 (0.70)			0.00 (-0.05, 0.06)	0.04 (0.97)		
Model 1 statistics			0.01	F(1, 4862) = 0.71 *p* = 0.4			0.00	F(1, 4860) = 0.15 *p* = 0.70			0.00	F(1, 2527) = 0.00 *p* = 0.97
Model 2: Urban-rural classification + green space												
Urban-rural classification	-0.02 (-0.05, 0.02)	-0.95 (0.34)			-0.03 (-0.06, 0.01)	-1.49 (0.14)			-0.01 (-0.05, 0.03)	-0.49 (0.63)		
Green space	0.00 (0.00, 0.01)	1.33 (0.18)			0.00 (0.00, 0.01)	1.39 (0.17)			0.00 (0.00, 0.01)	0.45 (0.65)		
Model 2 statistics			0.05	F(2, 4861) = 1.31 *p* = 0.27			0.05	F(2, 4859) = 1.11 *p* = 0.33			0.01	F(2, 2526) = 0.12 *p* = 0.89
Model 3: Urban-rural classification + green space + scenic level												
Urban-rural classification	-0.02 (-0.05, 0.02)	-0.89 (0.38)			-0.03 (-0.07, 0.00)	-1.81 (0.07)			-0.01 (-0.05, 0.03)	-0.54 (0.59)		
Green space	0.00 (0.00, 0.01)	1.32 (0.19)			0.00 (0.00, 0.01)	1.19 (0.23)			0.00 (0.00, 0.01)	0.40 (0.69)		
Scenic level	0.00 (-0.08, 0.08)	-0.04 (0.97)			0.05 (-0.03, 0.14)	1.25 (0.21)			0.01 (-0.08, 0.11)	0.25 (0.80)		
Model 3 statistics			0.05	F(3, 4860) = 0.87 *p* = 0.45			0.08	F(3, 4858) = 1.26 *p* = 0.29			0.01	F(3, 2525) = 0.10 *p* = 0.96
Difference in Model 2 and Model 3			ΔR^2 = 0.00	F(1, 4860) = 0.00 *p* = 0.97			ΔR^2 = 0.03	F(1, 4858) = 1.57 *p* = 0.21			ΔR^2 = 0.00	F(1, 2525) = 0.06 *p* = 0.80

9 km	'there are lots of fun things to do where I live' (n = 2528)				'I wish I lived in a different house' (n = 2523)			
	β (95% CIs)	t-value (*p*)	R^2	F statistic	β (95% CIs)	t-value (*p*)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.21 (-0.31, -0.11)	-4.03 (5.62 x10^{5})			0.04 (-0.07, 0.16)	0.76 (0.45)		
Model 1 statistics			0.64	F(1, 2526) = 16.28 *p* = 5.62 x10^{5}			0.02	F(1, 2521) = 0.58 *p* = 0.45
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.06 (-0.01, 0.13)	1.79 (0.07)			0.00 (-0.08, 0.07)	-0.10 (0.92)		
Green space	-0.01 (-0.02, -0.01)	-3.76 (0.0002)			0.00 (-0.01, 0.01)	0.00 (1.00)		
Model 2 statistics			1.69	F(2, 2525) = 21.72 *p* = 4.43 x10^{10}			0.00	F(2, 2520) = 0.05 *p* = 0.95
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	0.05 (-0.02, 0.12)	1.35 (0.18)			-0.03 (-0.11, 0.06)	-0.62 (0.53)		
Green space	-0.02 (-0.02, -0.01)	-3.91 (9.59 x10^{5})			0.00 (-0.01, 0.01)	-0.28 (0.78)		
Scenic level	0.11 (-0.07, 0.28)	1.21 (0.23)			0.18 (-0.02, 0.37)	1.77 (0.08)		
Model 3 statistics			1.75	F(3, 2524) = 14.97 *p* = 1.17 x10^{10}			0.13	F(3, 2519) = 1.08 *p* = 0.36
Difference in Model 2 and Model 3			ΔR^2 = 0.06	F(1, 2524) = 1.46 *p* = 0.23			ΔR^2 = 0.12	F(1, 2519) = 3.13 *p* = 0.08

9 km	'I wish there were different people in my neighbourhood' (n = 2525)				'I like where I live' (n = 2524)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.10 (-0.21, 0.01)	-1.82 (0.07)			0.06 (-0.02, 0.15)	1.44 (0.15)		
Model 1 statistics			0.13	F(1, 2523) = 3.31 p = 0.07			0.08	F(1, 2522) = 2.06 p = 0.15
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.02 (-0.06, 0.09)	0.40 (0.69)			0.00 (-0.06, 0.06)	0.06 (0.95)		
Green space	-0.01 (-0.01, 0.00)	-1.29 (0.20)			0.00 (-0.01, 0.01)	-0.06 (0.95)		
Model 2 statistics			0.32	F(2, 2522) = 4.00 p = 0.02			0.00	F(2, 2521) = 0.00 p = 1.00
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	0.01 (-0.07, 0.09)	0.20 (0.84)			-0.02 (-0.08, 0.04)	-0.69 (0.49)		
Green space	-0.01 (-0.01, 0.00)	-1.37 (0.17)			0.00 (-0.01, 0.01)	-0.46 (0.64)		
Scenic level	0.06 (-0.13, 0.24)	0.60 (0.55)			0.19 (0.04, 0.34)	2.52 (0.01)		
Model 3 statistics			0.33	F(3, 2521) = 2.79 p = 0.04			0.25	F(3, 2520) = 2.12 p = 0.10
Difference in Model 2 and Model 3			ΔR^2 = 0.01	F(1, 2521) = 0.37 p = 0.55			ΔR^2 = 0.25	F(1, 2520) = 6.37 p = 0.01

10 km	Subjective Happiness (n = 4930)				Life Satisfaction (n = 4928)				Subjective Health (n = 2553)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only												
Scenic	0.02 (-0.03, 0.07)	0.72 (0.47)			0.00 (-0.05, 0.05)	0.05 (0.96)			0.00 (-0.06, 0.06)	-0.03 (0.97)		
Model 1 statistics			0.01	F(1, 4862) = 0.51 $p = 0.47$			0.00	F(1, 4860) = 0.00 $p = 0.96$			0.00	F(1, 2527) = 0.00 $p = 0.97$
Model 2: Urban-rural classification + green space												
Urban-rural classification	-0.02 (-0.05, 0.01)	-1.12 (0.26)			-0.03 (-0.06, 0.01)	-1.54 (0.12)			-0.01 (-0.05, 0.03)	-0.28 (0.78)		
Green space	0.00 (0.00, 0.01)	1.50 (0.13)			0.00 (0.00, 0.01)	1.42 (0.16)			0.00 (0.00, 0.01)	0.23 (0.82)		
Model 2 statistics			0.06	F(2, 4861) = 1.54 $p = 0.21$			0.05	F(2, 4859) = 1.20 $p = 0.30$			0.00	F(2, 2526) = 0.05 $p = 0.95$
Model 3: Urban-rural classification + green space + scenic level												
Urban-rural classification	-0.02 (-0.05, 0.02)	-0.98 (0.33)			-0.03 (-0.07, 0.00)	-1.73 (0.08)			-0.01 (-0.05, 0.04)	-0.34 (0.74)		
Green space	0.00 (0.00, 0.01)	1.51 (0.13)			0.00 (0.00, 0.01)	1.31 (0.19)			0.00 (0.00, 0.01)	0.20 (0.85)		
Scenic level	-0.01 (-0.09, 0.07)	-0.23 (0.82)			0.04 (-0.05, 0.12)	0.82 (0.41)			0.01 (-0.09, 0.11)	0.22 (0.83)		
Model 3 statistics			0.06	F(3, 4860) = 1.04 $p = 0.37$			0.06	F(3, 4858) = 1.03 $p = 0.38$			0.01	F(3, 2525) = 0.05 $p = 0.99$
Difference in Model 2 and Model 3			$\Delta R^2 =$ 0.00	F(1, 4860) = 0.05 $p = 0.82$			$\Delta R^2 =$ 0.01	F(1, 4858) = 0.67 $p = 0.41$			$\Delta R^2 =$ 0.00	F(1, 2525) = 0.05 $p = 0.83$

10 km	'there are lots of fun things to do where I live' (n = 2528)				'I wish I lived in a different house' (n = 2523)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.21 (-0.32, -0.11)	-4.13 (3.81×10^{5})			0.04 (-0.08, 0.15)	0.63 (0.53)		
Model 1 statistics			0.67	F(1, 2526) = 17.03 $p = 3.81 \times 10^{5}$			0.02	F(1, 2521) = 0.39 $p = 0.53$
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.07 (0.00, 0.14)	1.86 (0.06)			0.01 (-0.07, 0.09)	0.20 (0.84)		
Green space	-0.02 (-0.02, -0.01)	-3.74 (0.0002)			0.00 (-0.01, 0.01)	-0.32 (0.75)		
Model 2 statistics			1.63	F(2, 2525) = 20.97 $p = 9.29 \times 10^{10}$			0.01	F(2, 2520) = 0.10 $p = 0.90$
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	0.06 (-0.02, 0.14)	1.52 (0.13)			-0.01 (-0.10, 0.07)	-0.30 (0.76)		
Green space	-0.02 (-0.02, -0.01)	-3.81 (0.0001)			0.00 (-0.01, 0.01)	-0.53 (0.6)		
Scenic level	0.07 (-0.11, 0.25)	0.79 (0.43)			0.16 (-0.04, 0.36)	1.59 (0.11)		
Model 3 statistics			1.66	F(3, 2524) = 14.18 $p = 3.63 \times 10^{9}$			0.11	F(3, 2519) = 0.91 $p = 0.43$
Difference in Model 2 and Model 3			$\Delta R^2 = 0.02$	F(1, 2524) = 0.62 $p = 0.43$			$\Delta R^2 = 0.10$	F(1, 2519) = 2.54 $p = 0.11$

10 km	'I wish there were different people in my neighbourhood' (n = 2525)				'I like where I live' (n = 2524)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.11 (-0.22, 0.00)	-1.95 (0.05)			0.06 (-0.03, 0.14)	1.29 (0.20)		
Model 1 statistics			0.15	F(1, 2523) = 3.80 p = 0.05			0.07	F(1, 2522) = 1.66 p = 0.20
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.03 (-0.05, 0.10)	0.63 (0.53)			0.01 (-0.06, 0.07)	0.16 (0.87)		
Green space	-0.01 (-0.02, 0.00)	-1.49 (0.14)			0.00 (-0.01, 0.01)	-0.16 (0.87)		
Model 2 statistics			0.33	F(2, 2522) = 4.17 p = 0.02			0.00	F(2, 2521) = 0.01 p = 0.99
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	0.02 (-0.06, 0.10)	0.50 (0.62)			-0.02 (-0.08, 0.05)	-0.53 (0.60)		
Green space	-0.01 (-0.02, 0.00)	-1.52 (0.13)			0.00 (-0.01, 0.01)	-0.46 (0.65)		
Scenic level	0.03 (-0.16, 0.22)	0.32 (0.75)			0.17 (0.02, 0.32)	2.22 (0.03)		
Model 3 statistics			0.33	F(3, 2521) = 2.81 p = 0.04			0.20	F(3, 2520) = 1.64 p = 0.18
Difference in Model 2 and Model 3			ΔR^2 = 0.00	F(1, 2521) = 0.10 p = 0.75			ΔR^2 = 0.19	F(1, 2520) = 4.91 p = 0.03

11 km	Subjective Happiness (n = 4930)				Life Satisfaction (n = 4928)				Subjective Health (n = 2553)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only												
Scenic	0.01 (-0.04, 0.06)	0.55 (0.58)			-0.01 (-0.06, 0.04)	-0.30 (0.76)			0.00 (-0.06, 0.05)	-0.14 (0.89)		
Model 1 statistics			0.01	F(1, 4862) = 0.31 p = 0.58			0.00	F(1, 4860) = 0.09 p = 0.76			0.00	F(1, 2527) = 0.02 p = 0.89
Model 2: Urban-rural classification + green space												
Urban-rural classification	-0.02 (-0.06, 0.01)	-1.15 (0.25)			-0.02 (-0.06, 0.01)	-1.30 (0.19)			-0.01 (-0.05, 0.04)	-0.27 (0.79)		
Green space	0.00 (0.00, 0.01)	1.50 (0.13)			0.00 (0.00, 0.01)	1.13 (0.26)			0.00 (0.00, 0.01)	0.21 (0.83)		
Model 2 statistics			0.06	F(2, 4861) = 1.52 p = 0.22			0.04	F(2, 4859) = 0.89 p = 0.41			0.00	F(2, 2526) = 0.05 p = 0.95
Model 3: Urban-rural classification + green space + scenic level												
Urban-rural classification	-0.02 (-0.06, 0.02)	-0.94 (0.35)			-0.03 (-0.06, 0.01)	-1.35 (0.18)			-0.01 (-0.05, 0.04)	-0.27 (0.78)		
Green space	0.00 (0.00, 0.01)	1.54 (0.12)			0.00 (0.00, 0.01)	1.08 (0.28)			0.00 (0.00, 0.01)	0.20 (0.84)		
Scenic level	-0.02 (-0.10, 0.07)	-0.44 (0.66)			0.02 (-0.07, 0.10)	0.38 (0.71)			0.00 (-0.10, 0.10)	0.06 (0.96)		
Model 3 statistics			0.07	F(3, 4860) = 1.07 p = 0.36			0.04	F(3, 4858) = 0.64 p = 0.59			0.00	F(3, 2525) = 0.03 p = 0.99
Difference in Model 2 and Model 3			ΔR^2 = 0.00	F(1, 4860) = 0.19 p = 0.66			ΔR^2 = 0.00	F(1, 4858) = 0.14 p = 0.71			ΔR^2 = 0.00	F(1, 2525) = 0.00 p = 0.96

11 km	'there are lots of fun things to do where I live' (n = 2528)				'I wish I lived in a different house' (n = 2523)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.22 (-0.33, -0.12)	-4.24 (2.30 x10^5)			0.03 (-0.09, 0.14)	0.45 (0.65)		
Model 1 statistics			0.71	F(1, 2526) = 17.99 p = 2.30 x10^5			0.01	F(1, 2521) = 0.21 p = 0.65
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.09 (0.01, 0.16)	2.25 (0.02)			0.02 (-0.07, 0.1)	0.40 (0.69)		
Green space	-0.02 (-0.03, -0.01)	-4.07 (4.90 x10^5)			0.00 (-0.01, 0.01)	-0.54 (0.59)		
Model 2 statistics			1.68	F(2, 2525) = 21.57 p = 5.14 x10^{10}			0.02	F(2, 2520) = 0.21 p = 0.81
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	0.08 (0, 0.16)	2.00 (0.05)			0.00 (-0.09, 0.09)	-0.05 (0.96)		
Green space	-0.02 (-0.03, -0.01)	-4.08 (4.56 x10^5)			0.00 (-0.01, 0.01)	-0.70 (0.48)		
Scenic level	0.04 (-0.14, 0.22)	0.39 (0.70)			0.14 (-0.06, 0.34)	1.37 (0.17)		
Model 3 statistics			1.69	F(3, 2524) = 14.43 p = 2.56 x10^9			0.09	F(3, 2519) = 0.76 p = 0.51
Difference in Model 2 and Model 3			ΔR^2 = 0.01	F(1, 2524) = 0.15 p = 0.70			ΔR^2 = 0.07	F(1, 2519) = 1.87 p = 0.17

11 km	'I wish there were different people in my neighbourhood' (n = 2525)				'I like where I live' (n = 2524)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.12 (-0.23, -0.01)	-2.1 (0.04)			0.05 (-0.04, 0.14)	1.11 (0.27)		
Model 1 statistics			0.17	F(1, 2523) = 4.42 p = 0.04			0.05	F(1, 2522) = 1.23 p = 0.27
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.04 (-0.04, 0.12)	0.90 (0.37)			0.01 (-0.06, 0.07)	0.24 (0.81)		
Green space	-0.01 (-0.02, 0.00)	-1.74 (0.08)			0.00 (-0.01, 0.01)	-0.22 (0.83)		
Model 2 statistics			0.35	F(2, 2522) = 4.44 p = 0.01			0.00	F(2, 2521) = 0.03 p = 0.97
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	0.04 (-0.05, 0.12)	0.86 (0.39)			-0.01 (-0.08, 0.05)	-0.36 (0.72)		
Green space	-0.01 (-0.02, 0.00)	-1.73 (0.08)			0.00 (-0.01, 0.01)	-0.44 (0.66)		
Scenic level	0.00 (-0.20, 0.19)	-0.02 (0.98)			0.14 (-0.01, 0.29)	1.85 (0.06)		
Model 3 statistics			0.35	F(3, 2521) = 2.96 p = 0.03			0.14	F(3, 2520) = 1.16 p = 0.32
Difference in Model 2 and Model 3			ΔR^2 = 0.00	F(1, 2521) = 0.00 p = 0.98			ΔR^2 = 0.14	F(1, 2520) = 3.42 p = 0.06

12 km	Subjective Happiness (n = 4930)				Life Satisfaction (n = 4928)				Subjective Health (n = 2553)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only												
Scenic	0.01 (-0.04, 0.06)	0.51 (0.61)			-0.01 (-0.06, 0.04)	-0.51 (0.61)			-0.01 (-0.06, 0.05)	-0.21 (0.84)		
Model 1 statistics			0.01	F(1, 4862) = 0.26 p = 0.61			0.01	F(1, 4860) = 0.26 p = 0.61			0.00	F(1, 2527) = 0.04 p = 0.84
Model 2: Urban-rural classification + green space												
Urban-rural classification	-0.03 (-0.06, 0.01)	-1.41 (0.16)			-0.02 (-0.06, 0.02)	-1.11 (0.27)			0.00 (-0.05, 0.04)	-0.13 (0.90)		
Green space	0.00 (0.00, 0.01)	1.76 (0.08)			0.00 (0.00, 0.01)	0.91 (0.36)			0.00 (0.00, 0.00)	0.05 (0.96)		
Model 2 statistics			0.08	F(2, 4861) = 1.89 p = 0.15			0.03	F(2, 4859) = 0.73 p = 0.48			0.00	F(2, 2526) = 0.04 p = 0.97
Model 3: Urban-rural classification + green space + scenic level												
Urban-rural classification	-0.02 (-0.06, 0.02)	-1.18 (0.24)			-0.02 (-0.06, 0.02)	-1.10 (0.27)			0.00 (-0.05, 0.04)	-0.13 (0.90)		
Green space	0.00 (0.00, 0.01)	1.79 (0.07)			0.00 (0.00, 0.01)	0.89 (0.37)			0.00 (0.00, 0.01)	0.05 (0.96)		
Scenic level	-0.02 (-0.11, 0.07)	-0.44 (0.66)			0.01 (-0.08, 0.10)	0.16 (0.88)			0.00 (-0.10, 0.10)	0.01 (0.99)		
Model 3 statistics			0.08	F(3, 4860) = 1.32 p = 0.27			0.03	F(3, 4858) = 0.49 p = 0.69			0.00	F(3, 2525) = 0.02 p = 1.00
Difference in Model 2 and Model 3			ΔR^2 = 0.00	F(1, 4860) = 0.20 p = 0.66			ΔR^2 = 0.00	F(1, 4858) = 0.02 p = 0.88			ΔR^2 = 0.00	F(1, 2525) = 0.00 p = 0.99

12 km	‘there are lots of fun things to do where I live’ (n = 2528)				‘I wish I lived in a different house’ (n = 2523)			
	β (95% CIs)	t-value (*p*)	R^2	F statistic	β (95% CIs)	t-value (*p*)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.23 (-0.33, -0.12)	-4.27 (2.02 x10^{5})			0.03 (-0.09, 0.15)	0.47 (0.64)		
Model 1 statistics			0.72	F(1, 2526) = 18.24 *p* = 2.02 x10^{5}			0.01	F(1, 2521) = 0.22 *p* = 0.64
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.10 (0.02, 0.18)	2.51 (0.01)			0.03 (-0.06, 0.12)	0.62 (0.54)		
Green space	-0.02 (-0.03, -0.01)	-4.28 (1.93 x10^{5})			0.00 (-0.01, 0.01)	-0.77 (0.44)		
Model 2 statistics			1.70	F(2, 2525) = 21.88 *p* = 3.78 x10^{10}			0.03	F(2, 2520) = 0.36 *p* = 0.70
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	0.10 (0.02, 0.18)	2.33 (0.02)			0.01 (-0.09, 0.10)	0.14 (0.89)		
Green space	-0.02 (-0.03, -0.01)	-4.27 (2.02 x10^{5})			0.00 (-0.01, 0.01)	-0.91 (0.36)		
Scenic level	0.01 (-0.17, 0.19)	0.14 (0.89)			0.15 (-0.06, 0.35)	1.41 (0.16)		
Model 3 statistics			1.70	F(3, 2524) = 14.59 *p* = 2.02 x10^{9}			0.11	F(3, 2519) = 0.90 *p* = 0.44
Difference in Model 2 and Model 3			ΔR^2 = 0.00	F(1, 2524) = 0.02 *p* = 0.89			ΔR^2 = 0.08	F(1, 2519) = 1.99 *p* = 0.16

12 km	'I wish there were different people in my neighbourhood' (n = 2525)				'I like where I live' (n = 2524)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.13 (-0.24, -0.01)	-2.2 (0.03)			0.05 (-0.04, 0.14)	1.05 (0.29)		
Model 1 statistics			0.19	F(1, 2523) = 4.83 p = 0.03			0.04	F(1, 2522) = 1.10 p = 0.29
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.06 (-0.03, 0.14)	1.30 (0.19)			0.01 (-0.05, 0.08)	0.40 (0.69)		
Green space	-0.01 (-0.02, 0.00)	-2.13 (0.03)			0.00 (-0.01, 0.01)	-0.37 (0.71)		
Model 2 statistics			0.40	F(2, 2522) = 5.08 p = 0.01			0.01	F(2, 2521) = 0.08 p = 0.92
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	0.06 (-0.03, 0.15)	1.31 (0.19)			-0.01 (-0.07, 0.06)	-0.15 (0.88)		
Green space	-0.01 (-0.02, 0.00)	-2.1 (0.04)			0.00 (-0.01, 0.01)	-0.55 (0.58)		
Scenic level	-0.02 (-0.22, 0.17)	-0.24 (0.81)			0.13 (-0.02, 0.28)	1.66 (0.10)		
Model 3 statistics			0.40	F(3, 2521) = 3.40 p = 0.02			0.12	F(3, 2520) = 0.97 p = 0.40
Difference in Model 2 and Model 3			ΔR^2 = 0.00	F(1, 2521) = 0.06 p = 0.81			ΔR^2 = 0.11	F(1, 2520) = 2.76 p = 0.10

13 km	Subjective Happiness (n = 4930)				Life Satisfaction (n = 4928)				Subjective Health (n = 2553)			
	β (95% CIs)	t-value (*p*)	R^2	F statistic	β (95% CIs)	t-value (*p*)	R^2	F statistic	β (95% CIs)	t-value (*p*)	R^2	F statistic
Model 1: Scenic only												
Scenic	0.01 (-0.04, 0.06)	0.41 (0.68)			-0.02 (-0.07, 0.03)	-0.72 (0.47)			-0.01 (-0.07, 0.05)	-0.27 (0.79)		
Model 1 statistics			0.00	F(1, 4862) = 0.17 *p* = 0.68			0.01	F(1, 4860) = 0.51 *p* = 0.47			0.00	F(1, 2527) = 0.07 *p* = 0.79
Model 2: Urban-rural classification + green space												
Urban-rural classification	-0.03 (-0.07, 0.00)	-1.78 (0.07)			-0.02 (-0.06, 0.02)	-1.16 (0.25)			0.00 (-0.05, 0.04)	-0.08 (0.93)		
Green space	0.00 (0.00, 0.01)	2.12 (0.03)			0.00 (0.00, 0.01)	0.94 (0.35)			0.00 (-0.01, 0.00)	-0.02 (0.98)		
Model 2 statistics			0.10	F(2, 4861) = 2.54 *p* = 0.08			0.03	F(2, 4859) = 0.82 *p* = 0.44			0.00	F(2, 2526) = 0.06 *p* = 0.95
Model 3: Urban-rural classification + green space + scenic level												
Urban-rural classification	-0.03 (-0.07, 0.01)	-1.50 (0.13)			-0.02 (-0.06, 0.02)	-1.07 (0.29)			0.00 (-0.05, 0.04)	-0.08 (0.94)		
Green space	0.00 (0.00, 0.01)	2.16 (0.03)			0.00 (0.00, 0.01)	0.94 (0.35)			0.00 (-0.01, 0.00)	-0.02 (0.98)		
Scenic level	-0.02 (-0.11, 0.06)	-0.52 (0.60)			0.00 (-0.09, 0.09)	-0.08 (0.94)			0.00 (-0.10, 0.10)	0.00 (1.00)		
Model 3 statistics			0.11	F(3, 4860) = 1.78 *p* = 0.15			0.03	F(3, 4858) = 0.55 *p* = 0.65			0.00	F(3, 2525) = 0.04 *p* = 0.99
Difference in Model 2 and Model 3			ΔR^2 = 0.01	F(1, 4860) = 0.27 *p* = 0.60			ΔR^2 = 0.00	F(1, 4858) = 0.01 *p* = 0.94			ΔR^2 = 0.00	F(1, 2525) = 0.00 *p* = 1.00

13 km	**‘there are lots of fun things to do where I live’** (n = 2528)				**‘I wish I lived in a different house’** (n = 2523)			
	β (95% CIs)	t-value (*p*)	R^2	F statistic	β (95% CIs)	t-value (*p*)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.23 (-0.34, -0.12)	-4.24 (2.32 x10^{5})			0.03 (-0.09, 0.15)	0.51 (0.61)		
Model 1 statistics			0.71	F(1, 2526) = 17.97 *p* = 2.32 x10^{5}			0.01	F(1, 2521) = 0.26 *p* = 0.61
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.10 (0.02, 0.18)	2.54 (0.01)			0.03 (-0.06, 0.12)	0.60 (0.55)		
Green space	-0.02 (-0.03, -0.01)	-4.28 (1.98 x10^{5})			0.00 (-0.01, 0.01)	-0.75 (0.45)		
Model 2 statistics			1.68	F(2, 2525) = 21.62 *p* = 4.91 x10^{10}			0.03	F(2, 2520) = 0.35 *p* = 0.70
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	0.10 (0.02, 0.19)	2.38 (0.02)			0.00 (-0.09, 0.10)	0.10 (0.92)		
Green space	-0.02 (-0.03, -0.01)	-4.26 (2.08 x10^{5})			0.00 (-0.02, 0.01)	-0.90 (0.37)		
Scenic level	0.01 (-0.17, 0.19)	0.11 (0.91)			0.16 (-0.05, 0.37)	1.50 (0.13)		
Model 3 statistics			1.68	F(3, 2524) = 14.41 *p* = 2.62 x10^{9}			0.12	F(3, 2519) = 0.99 *p* = 0.40
Difference in Model 2 and Model 3			ΔR^2 = 0.00	F(1, 2524) = 0.01 *p* = 0.91			ΔR^2 = 0.09	F(1, 2519) = 2.26 *p* = 0.13

13 km	'I wish there were different people in my neighbourhood' (n = 2525)				'I like where I live' (n = 2524)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.13 (-0.24, -0.01)	-2.17 (0.03)			0.04 (-0.05, 0.13)	0.97 (0.33)		
Model 1 statistics			0.19	F(1, 2523) = 4.72 p = 0.03			0.04	F(1, 2522) = 0.95 p = 0.33
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.06 (-0.02, 0.15)	1.41 (0.16)			0.02 (-0.05, 0.08)	0.48 (0.63)		
Green space	-0.01 (-0.02, 0.00)	-2.22 (0.03)			0.00 (-0.01, 0.01)	-0.44 (0.66)		
Model 2 statistics			0.41	F(2, 2522) = 5.18 p = 0.01			0.01	F(2, 2521) = 0.12 p = 0.89
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	0.07 (-0.03, 0.16)	1.41 (0.16)			0.00 (-0.07, 0.07)	0.00 (1.00)		
Green space	-0.01 (-0.02, 0.00)	-2.18 (0.03)			0.00 (-0.01, 0.01)	-0.59 (0.55)		
Scenic level	-0.02 (-0.22, 0.17)	-0.24 (0.81)			0.12 (-0.04, 0.27)	1.46 (0.15)		
Model 3 statistics			0.41	F(3, 2521) = 3.47 p = 0.02			0.09	F(3, 2520) = 0.79 p = 0.50
Difference in Model 2 and Model 3			ΔR^2 = 0.00	F(1, 2521) = 0.06 p = 0.81			ΔR^2 = 0.08	F(1, 2520) = 2.12 p = 0.15

14 km	Subjective Happiness (n = 4930)				Life Satisfaction (n = 4928)				Subjective Health (n = 2553)			
	β (95% CIs)	t-value (*p*)	R^2	F statistic	β (95% CIs)	t-value (*p*)	R^2	F statistic	β (95% CIs)	t-value (*p*)	R^2	F statistic
Model 1: Scenic only												
Scenic	0.01 (-0.04, 0.06)	0.32 (0.75)			-0.02 (-0.08, 0.03)	-0.87 (0.38)			-0.01 (-0.07, 0.05)	-0.34 (0.73)		
Model 1 statistics			0.00	F(1, 4862) = 0.11 *p* = 0.75			0.02	F(1, 4860) = 0.76 *p* = 0.38			0.00	F(1, 2527) = 0.12 *p* = 0.73
Model 2: Urban-rural classification + green space												
Urban-rural classification	-0.04 (-0.07, 0.00)	-1.81 (0.07)			-0.02 (-0.06, 0.02)	-1.13 (0.26)			0.00 (-0.04, 0.05)	0.10 (0.92)		
Green space	0.00 (0.00, 0.01)	2.13 (0.03)			0.00 (0.00, 0.01)	0.89 (0.38)			0.00 (-0.01, 0.00)	-0.23 (0.82)		
Model 2 statistics			0.10	F(2, 4861) = 2.50 *p* = 0.08			0.03	F(2, 4859) = 0.83 *p* = 0.44			0.01	F(2, 2526) = 0.09 *p* = 0.91
Model 3: Urban-rural classification + green space + scenic level												
Urban-rural classification	-0.03 (-0.07, 0.01)	-1.50 (0.13)			-0.02 (-0.06, 0.02)	-0.97 (0.33)			0.00 (-0.04, 0.05)	0.11 (0.91)		
Green space	0.00 (0.00, 0.01)	2.16 (0.03)			0.00 (0.00, 0.01)	0.90 (0.37)			0.00 (-0.01, 0.00)	-0.22 (0.83)		
Scenic level	-0.03 (-0.11, 0.06)	-0.58 (0.56)			-0.01 (-0.10, 0.08)	-0.26 (0.80)			0.00 (-0.11, 0.10)	-0.05 (0.96)		
Model 3 statistics			0.11	F(3, 4860) = 1.78 *p* = 0.15			0.04	F(3, 4858) = 0.57 *p* = 0.63			0.01	F(3, 2525) = 0.06 *p* = 0.98
Difference in Model 2 and Model 3			ΔR^2 = 0.01	F(1, 4860) = 0.34 *p* = 0.56			ΔR^2 = 0.00	F(1, 4858) = 0.07 *p* = 0.80			ΔR^2 = 0.00	F(1, 2525) = 0.00 *p* = 0.96

14 km	'there are lots of fun things to do where I live' (n = 2528)				'I wish I lived in a different house' (n = 2523)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.24 (-0.35, -0.13)	-4.31 (1.69 x10^5)			0.03 (-0.09, 0.15)	0.44 (0.66)		
Model 1 statistics			0.73	F(1, 2526) = 18.58 p = 1.69 x10^5			0.01	F(1, 2521) = 0.19 p = 0.66
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.11 (0.03, 0.19)	2.60 (0.01)			0.03 (-0.07, 0.12)	0.53 (0.60)		
Green space	-0.02 (-0.03, -0.01)	-4.31 (1.67 x10^5)			0.00 (-0.01, 0.01)	-0.67 (0.50)		
Model 2 statistics			1.68	F(2, 2525) = 21.53 p = 1.69 x10^{10}			0.02	F(2, 2520) = 0.28 p = 0.75
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	0.11 (0.02, 0.20)	2.50 (0.01)			0.00 (-0.09, 0.10)	0.10 (0.92)		
Green space	-0.02 (-0.03, -0.01)	-4.28 (1.93 x10^5)			0.00 (-0.01, 0.01)	-0.80 (0.42)		
Scenic level	-0.01 (-0.19, 0.18)	-0.09 (0.93)			0.14 (-0.07, 0.35)	1.31 (0.19)		
Model 3 statistics			1.68	F(3, 2524) = 14.35 p = 2.86 x10^9			0.09	F(3, 2519) = 0.76 p = 0.52
Difference in Model 2 and Model 3			ΔR^2 = 0.00	F(1, 2524) = 0.01 p = 0.93			ΔR^2 = 0.07	F(1, 2519) = 1.72 p = 0.19

14 km	'I wish there were different people in my neighbourhood' (n = 2525)				'I like where I live' (n = 2524)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.13 (-0.25, -0.02)	-2.27 (0.02)			0.04 (-0.05, 0.13)	0.93 (0.35)		
Model 1 statistics			0.20	F(1, 2523) = 5.17 p = 0.02			0.03	F(1, 2522) = 0.86 p = 0.35
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.07 (-0.02, 0.16)	1.51 (0.13)			0.02 (-0.05, 0.09)	0.55 (0.58)		
Green space	-0.01 (-0.02, 0.00)	-2.31 (0.02)			0.00 (-0.01, 0.01)	-0.49 (0.62)		
Model 2 statistics			0.41	F(2, 2522) = 5.25 p = 0.01			0.01	F(2, 2521) = 0.16 p = 0.85
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	0.08 (-0.02, 0.17)	1.59 (0.11)			0.00 (-0.07, 0.08)	0.13 (0.90)		
Green space	-0.01 (-0.02, 0.00)	-2.24 (0.02)			0.00 (-0.01, 0.01)	-0.62 (0.54)		
Scenic level	-0.05 (-0.25, 0.15)	-0.50 (0.62)			0.10 (-0.06, 0.26)	1.27 (0.21)		
Model 3 statistics			0.42	F(3, 2521) = 3.58 p = 0.01			0.08	F(3, 2520) = 0.64 p = 0.59
Difference in Model 2 and Model 3			ΔR^2 = 0.01	F(1, 2521) = 0.25 p = 0.62			ΔR^2 = 0.06	F(1, 2520) = 1.61 p = 0.21

15 km	Subjective Happiness (n = 4930)				Life Satisfaction (n = 4928)				Subjective Health (n = 2553)			
	β (95% CIs)	t-value (*p*)	R^2	F statistic	β (95% CIs)	t-value (*p*)	R^2	F statistic	β (95% CIs)	t-value (*p*)	R^2	F statistic
Model 1: Scenic only												
Scenic	0.00 (-0.05, 0.06)	0.18 (0.86)			-0.03 (-0.08, 0.03)	-0.99 (0.32)			-0.01 (-0.07, 0.05)	-0.42 (0.67)		
Model 1 statistics			0.00	F(1, 4862) = 0.03 *p* = 0.86			0.02	F(1, 4860) = 0.98 *p* = 0.32			0.01	F(1, 2527) = 0.18 *p* = 0.67
Model 2: Urban-rural classification + green space												
Urban-rural classification	-0.04 (-0.08, 0.00)	-1.92 (0.05)			-0.02 (-0.06, 0.02)	-1.18 (0.24)			0.01 (-0.04, 0.05)	0.22 (0.82)		
Green space	0.01 (0.00, 0.01)	2.22 (0.03)			0.00 (0.00, 0.01)	0.92 (0.36)			0.00 (-0.01, 0.00)	-0.35 (0.72)		
Model 2 statistics			0.11	F(2, 4861) = 2.66 *p* = 0.07			0.04	F(2, 4859) = 0.91 *p* = 0.40			0.01	F(2, 2526) = 0.13 *p* = 0.88
Model 3: Urban-rural classification + green space + scenic level												
Urban-rural classification	-0.03 (-0.07, 0.01)	-1.55 (0.12)			-0.02 (-0.06, 0.02)	-0.98 (0.33)			0.01 (-0.04, 0.06)	0.26 (0.79)		
Green space	0.01 (0.00, 0.01)	2.26 (0.02)			0.00 (0, 0.01)	0.95 (0.34)			0.00 (-0.01, 0.00)	-0.33 (0.74)		
Scenic level	-0.03 (-0.12, 0.06)	-0.70 (0.48)			-0.02 (-0.11, 0.07)	-0.38 (0.70)			-0.01 (-0.11, 0.10)	-0.17 (0.87)		
Model 3 statistics			0.12	F(3, 4860) = 1.94 *p* = 0.12			0.04	F(3, 4858) = 0.66 *p* = 0.58			0.01	F(3, 2525) = 0.10 *p* = 0.96
Difference in Model 2 and Model 3			ΔR^2 = 0.01	F(1, 4860) = 0.49 *p* = 0.48			ΔR^2 = 0.00	F(1, 4858) = 0.15 *p* = 0.70			ΔR^2 = 0.00	F(1, 2525) = 0.03 *p* = 0.87

15 km	'there are lots of fun things to do where I live' (n = 2528)				'I wish I lived in a different house' (n = 2523)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.25 (-0.36, -0.14)	-4.43 (9.96 x10^5)			0.03 (-0.10, 0.15)	0.42 (0.67)		
Model 1 statistics			0.77	F(1, 2526) = 19.60 p = 9.96 x10^5			0.01	F(1, 2521) = 0.18 p = 0.67
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.11 (0.03, 0.20)	2.65 (0.01)			0.02 (-0.08, 0.11)	0.40 (0.69)		
Green space	-0.02 (-0.03, -0.01)	-4.36 (1.37 x10^5)			0.00 (-0.01, 0.01)	-0.51 (0.61)		
Model 2 statistics			1.68	F(2, 2525) = 21.51 p = 5.46 x10^{10}			0.01	F(2, 2520) = 0.18 p = 0.84
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	0.12 (0.03, 0.21)	2.64 (0.01)			0.00 (-0.10, 0.10)	0.00 (1.00)		
Green space	-0.02 (-0.03, -0.01)	-4.30 (1.78 x10^5)			0 00 (-0.01, 0.01)	-0.63 (0.53)		
Scenic level	-0.04 (-0.23, 0.15)	-0.39 (0.70)			0.13 (-0.08, 0.34)	1.19 (0.23)		
Model 3 statistics			1.68	F(3, 2524) = 14.38 p = 2.72 x10^9			0.07	F(3, 2519) = 0.59 p = 0.62
Difference in Model 2 and Model 3			ΔR^2 = 0.01	F(1, 2524) = 0.15 p = 0.7			ΔR^2 = 0.06	F(1, 2519) = 1.42 p = 0.23

15 km	'I wish there were different people in my neighbourhood' (n = 2525)				'I like where I live' (n = 2524)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.14 (-0.26, -0.02)	-2.28 (0.02)			0.04 (-0.05, 0.13)	0.85 (0.39)		
Model 1 statistics			0.21	F(1, 2523) = 5.19 p = 0.02			0.03	F(1, 2522) = 0.73 p = 0.39
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.06 (-0.03, 0.15)	1.41 (0.16)			0.02 (-0.05, 0.09)	0.59 (0.55)		
Green space	-0.01 (-0.02, 0.00)	-2.19 (0.03)			0.00 (-0.01, 0.01)	-0.52 (0.60)		
Model 2 statistics			0.39	F(2, 2522) = 4.94 p = 0.01			0.01	F(2, 2521) = 0.19 p = 0.83
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	0.07 (-0.02, 0.17)	1.51 (0.13)			0.01 (-0.07, 0.08)	0.23 (0.82)		
Green space	-0.01 (-0.02, 0.00)	-2.13 (0.03)			0.00 (-0.01, 0.01)	-0.62 (0.54)		
Scenic level	-0.06 (-0.26, 0.14)	-0.56 (0.57)			0.09 (-0.07, 0.24)	1.05 (0.29)		
Model 3 statistics			0.40	F(3, 2521) = 3.4 p = 0.02			0.06	F(3, 2520) = 0.50 p = 0.69
Difference in Model 2 and Model 3			ΔR^2 = 0.01	F(1, 2521) = 0.32 p = 0.57			ΔR^2 = 0.04	F(1, 2520) = 1.11 p = 0.29

16 km	Subjective Happiness (n = 4930)				Life Satisfaction (n = 4928)				Subjective Health (n = 2553)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only												
Scenic	0.00 (-0.05, 0.05)	0.05 (0.96)			-0.03 (-0.09, 0.02)	-1.13 (0.26)			-0.01 (-0.08, 0.05)	-0.46 (0.65)		
Model 1 statistics			0.00	F(1, 4862) = 0.00 p = 0.96			0.03	F(1, 4860) = 1.27 p = 0.26			0.01	F(1, 2527) = 0.21 p = 0.65
Model 2: Urban-rural classification + green space												
Urban-rural classification	-0.04 (-0.08, -0.01)	-2.22 (0.03)			-0.03 (-0.07, 0.01)	-1.36 (0.17)			0.01 (-0.04, 0.06)	0.39 (0.70)		
Green space	0.01 (0.00, 0.01)	2.51 (0.01)			0.00 (0.00, 0.01)	1.08 (0.28)			0.00 (-0.01, 0.00)	-0.53 (0.60)		
Model 2 statistics			0.13	F(2, 4861) = 3.27 p = 0.04			0.05	F(2, 4859) = 1.18 p = 0.31			0.02	F(2, 2526) = 0.22 p = 0.80
Model 3: Urban-rural classification + green space + scenic level												
Urban-rural classification	-0.04 (-0.08, 0.00)	-1.81 (0.07)			-0.02 (-0.07, 0.02)	-1.11 (0.27)			0.01 (-0.04, 0.06)	0.42 (0.67)		
Green space	0.01 (0.00, 0.01)	2.54 (0.01)			0.00 (0.00, 0.01)	1.10 (0.27)			0.00 (-0.01, 0.00)	-0.51 (0.61)		
Scenic level	-0.04 (-0.13, 0.06)	-0.76 (0.45)			-0.02 (-0.12, 0.07)	-0.47 (0.64)			-0.01 (-0.12, 0.10)	-0.19 (0.85)		
Model 3 statistics			0.15	F(3, 4860) = 2.37 p = 0.07			0.05	F(3, 4858) = 0.86 p = 0.46			0.02	F(3, 2525) = 0.16 p = 0.93
Difference in Model 2 and Model 3			ΔR^2 = 0.01	F(1, 4860) = 0.58 p = 0.45			ΔR^2 = 0.00	F(1, 4858) = 0.22 p = 0.64			ΔR^2 = 0.00	F(1, 2525) = 0.03 p = 0.85

16 km	‘there are lots of fun things to do where I live’ (n = 2528)				‘I wish I lived in a different house’ (n = 2523)			
	β (95% CIs)	t-value (*p*)	R^2	F statistic	β (95% CIs)	t-value (*p*)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.26 (-0.37, -0.15)	-4.51 (6.66×10^{6})			0.02 (-0.10, 0.15)	0.39 (0.70)		
Model 1 statistics			0.80	$F(1, 2526) = 20.37$ $p = 6.66 \times 10^{6}$			0.01	$F(1, 2521) = 0.15$ $p = 0.70$
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.11 (0.03, 0.20)	2.63 (0.01)			0.01 (-0.08, 0.11)	0.27 (0.79)		
Green space	-0.02 (-0.03, -0.01)	-4.34 (1.49×10^{5})			0.00 (-0.01, 0.01)	-0.36 (0.72)		
Model 2 statistics			1.67	$F(2, 2525) = 21.44$ $p = 5.84 \times 10^{10}$			0.01	$F(2, 2520) = 0.10$ $p = 0.91$
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	0.12 (0.03, 0.21)	2.67 (0.01)			0.00 (-0.10, 0.10)	-0.07 (0.94)		
Green space	-0.02 (-0.03, -0.01)	-4.27 (2.05×10^{5})			0.00 (-0.01, 0.01)	-0.46 (0.65)		
Scenic level	-0.05 (-0.25, 0.14)	-0.56 (0.58)			0.11 (-0.10, 0.33)	1.04 (0.30)		
Model 3 statistics			1.68	$F(3, 2524) = 14.39$ $p = 2.68 \times 10^{9}$			0.05	$F(3, 2519) = 0.42$ $p = 0.74$
Difference in Model 2 and Model 3			$\Delta R^2 = 0.01$	$F(1, 2524) = 0.31$ $p = 0.58$			$\Delta R^2 = 0.04$	$F(1, 2519) = 1.08$ $p = 0.30$

16 km	'I wish there were different people in my neighbourhood' (n = 2525)				'I like where I live' (n = 2524)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.14 (-0.26, -0.02)	-2.26 (0.02)			0.04 (-0.06, 0.13)	0.81 (0.42)		
Model 1 statistics			0.20	F(1, 2523) = 5.10 p = 0.02			0.03	F(1, 2522) = 0.66 p = 0.42
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.05 (-0.04, 0.14)	1.09 (0.28)			0.01 (-0.06, 0.09)	0.39 (0.70)		
Green space	-0.01 (-0.02, 0.00)	-1.85 (0.06)			0.00 (-0.01, 0.01)	-0.29 (0.77)		
Model 2 statistics			0.33	F(2, 2522) = 4.20 p = 0.02			0.01	F(2, 2521) = 0.11 p = 0.90
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	0.06 (-0.04, 0.16)	1.22 (0.22)			0.00 (-0.07, 0.08)	0.07 (0.94)		
Green space	-0.01 (-0.02, 0.00)	-1.79 (0.07)			0.00 (-0.01, 0.01)	-0.38 (0.70)		
Scenic level	-0.06 (-0.27, 0.14)	-0.61 (0.55)			0.08 (-0.09, 0.24)	0.93 (0.35)		
Model 3 statistics			0.35	F(3, 2521) = 2.92 p = 0.03			0.04	F(3, 2520) = 0.36 p = 0.78
Difference in Model 2 and Model 3			ΔR^2 = 0.01	F(1, 2521) = 0.37 p = 0.55			ΔR^2 = 0.03	F(1, 2520) = 0.86 p = 0.35

17 km	Subjective Happiness (n = 4930)				Life Satisfaction (n = 4928)				Subjective Health (n = 2553)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only												
Scenic	0.00 (-0.05, 0.06)	0.11 (0.91)			-0.03 (-0.09, 0.02)	-1.11 (0.27)			-0.01 (-0.08, 0.05)	-0.46 (0.64)		
Model 1 statistics			0.00	F(1, 4862) = 0.01 p = 0.91			0.03	F(1, 4860) = 1.24 p = 0.27			0.01	F(1, 2527) = 0.21 p = 0.64
Model 2: Urban-rural classification + green space												
Urban-rural classification	-0.05 (-0.09, -0.01)	-2.23 (0.03)			-0.03 (-0.07, 0.01)	-1.37 (0.17)			0.01 (-0.04, 0.06)	0.38 (0.70)		
Green space	0.01 (0.00, 0.01)	2.48 (0.01)			0.00 (0.00, 0.01)	1.04 (0.30)			0.00 (-0.01, 0.00)	-0.53 (0.59)		
Model 2 statistics			0.13	F(2, 4861) = 3.15 p = 0.04			0.05	F(2, 4859) = 1.30 p = 0.27			0.02	F(2, 2526) = 0.23 p = 0.80
Model 3: Urban-rural classification + green space + scenic level												
Urban-rural classification	-0.04 (-0.09, 0.00)	-1.91 (0.06)			-0.03 (-0.07, 0.02)	-1.19 (0.23)			0.01 (-0.04, 0.06)	0.42 (0.68)		
Green space	0.01 (0.00, 0.01)	2.50 (0.01)			0.00 (0.00, 0.01)	1.05 (0.29)			0.00 (-0.01, 0.00)	-0.52 (0.60)		
Scenic level	-0.02 (-0.11, 0.07)	-0.49 (0.62)			-0.01 (-0.11, 0.08)	-0.25 (0.80)			-0.01 (-0.12, 0.10)	-0.17 (0.87)		
Model 3 statistics			0.13	F(3, 4860) = 2.18 p = 0.09			0.05	F(3, 4858) = 0.89 p = 0.45			0.02	F(3, 2525) = 0.16 p = 0.92
Difference in Model 2 and Model 3			ΔR^2 = 0.01	F(1, 4860) = 0.24 p = 0.62			ΔR^2 = 0.00	F(1, 4858) = 0.06 p = 0.80			ΔR^2 = 0.00	F(1, 2525) = 0.03 p = 0.87

17 km	'there are lots of fun things to do where I live' (n = 2528)				'I wish I lived in a different house' (n = 2523)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.26 (-0.37, -0.14)	-4.45 (9.09 x10^{6})			0.02 (-0.10, 0.15)	0.38 (0.70)		
Model 1 statistics			0.78	F(1, 2526) = 19.77 p = 9.09 x10^{6}			0.01	F(1, 2521) = 0.15 p = 0.70
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.12 (0.03, 0.20)	2.61 (0.01)			0.01 (-0.08, 0.11)	0.28 (0.78)		
Green space	-0.02 (-0.03, -0.01)	-4.33 (1.56 x10^{5})			0.00 (-0.01, 0.01)	-0.38 (0.70)		
Model 2 statistics			1.68	F(2, 2525) = 21.62 p = 4.90 x10^{10}			0.01	F(2, 2520) = 0.11 p = 0.90
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	0.12 (0.03, 0.21)	2.61 (0.01)			0.00 (-0.11, 0.10)	-0.06 (0.95)		
Green space	-0.02 (-0.03, -0.01)	-4.27 (1.99 x10^{5})			0.00 (-0.01, 0.01)	-0.47 (0.64)		
Scenic level	-0.04 (-0.23, 0.15)	-0.42 (0.68)			0.12 (-0.10, 0.33)	1.05 (0.29)		
Model 3 statistics			1.69	F(3, 2524) = 14.47 p = 2.41 x10^{9}			0.05	F(3, 2519) = 0.44 p = 0.73
Difference in Model 2 and Model 3			ΔR^2 = 0.01	F(1, 2524) = 0.17 p = 0.68			ΔR^2 = 0.04	F(1, 2519) = 1.10 p = 0.29

17 km	'I wish there were different people in my neighbourhood' (n = 2525)				'I like where I live' (n = 2524)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.14 (-0.26, -0.02)	-2.22 (0.03)			0.04 (-0.06, 0.13)	0.81 (0.42)		
Model 1 statistics			0.20	F(1, 2523) = 4.94 p = 0.03			0.03	F(1, 2522) = 0.65 p = 0.42
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.04 (-0.05, 0.14)	0.87 (0.38)			0.01 (-0.06, 0.09)	0.36 (0.72)		
Green space	-0.01 (-0.02, 0.00)	-1.65 (0.10)			0 .00 (-0.01, 0.01)	-0.28 (0.78)		
Model 2 statistics			0.31	F(2, 2522) = 3.98 p = 0.02			0.01	F(2, 2521) = 0.09 p = 0.91
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	0.05 (-0.05, 0.15)	0.98 (0.33)			0.00 (-0.08, 0.08)	0.04 (0.97)		
Green space	-0.01 (-0.02, 0.00)	-1.60 (0.11)			0.00 (-0.01, 0.01)	-0.37 (0.71)		
Scenic level	-0.05 (-0.26, 0.16)	-0.49 (0.62)			0.08 (-0.08, 0.24)	0.97 (0.33)		
Model 3 statistics			0.32	F(3, 2521) = 2.73 p = 0.04			0.04	F(3, 2520) = 0.37 p = 0.77
Difference in Model 2 and Model 3			ΔR^2 = 0.01	F(1, 2521) = 0.24 p = 0.62			ΔR^2 = 0.04	F(1, 2520) = 0.94 p = 0.33

18 km	Subjective Happiness (n = 4930)				Life Satisfaction (n = 4928)				Subjective Health (n = 2553)			
	β (95% CIs)	t-value (*p*)	R^2	F statistic	β (95% CIs)	t-value (*p*)	R^2	F statistic	β (95% CIs)	t-value (*p*)	R^2	F statistic
Model 1: Scenic only												
Scenic	0.00 (-0.05, 0.06)	0.09 (0.93)			-0.03 (-0.09, 0.02)	-1.14 (0.26)			-0.02 (-0.08, 0.05)	-0.52 (0.60)		
Model 1 statistics			0.00	F(1, 4862) = 0.01 *p* = 0.93			0.03	F(1, 4860) = 1.29 *p* = 0.26			0.01	F(1, 2527) = 0.27 *p* = 0.60
Model 2: Urban-rural classification + green space												
Urban-rural classification	-0.05 (-0.09, -0.01)	-2.23 (0.03)			-0.03 (-0.07, 0.01)	-1.40 (0.16)			0.01 (-0.04, 0.06)	0.22 (0.82)		
Green space	0.01 (0.00, 0.01)	2.46 (0.01)			0.00 (0.00, 0.01)	1.04 (0.30)			0.00 (-0.01, 0.00)	-0.39 (0.70)		
Model 2 statistics			0.13	F(2, 4861) = 3.07 *p* = 0.05			0.06	F(2, 4859) = 1.42 *p* = 0.24			0.02	F(2, 2526) = 0.20 *p* = 0.82
Model 3: Urban-rural classification + green space + scenic level												
Urban-rural classification	-0.04 (-0.09, 0.00)	-1.93 (0.05)			-0.03 (-0.08, 0.02)	-1.25 (0.21)			0.01 (-0.05, 0.06)	0.27 (0.79)		
Green space	0.01 (0.00, 0.01)	2.47 (0.01)			0.00 (0.00, 0.01)	1.05 (0.30)			0.00 (-0.01, 0.00)	-0.37 (0.71)		
Scenic level	-0.02 (-0.11, 0.07)	-0.41 (0.68)			-0.01 (-0.10, 0.09)	-0.16 (0.88)			-0.01 (-0.12, 0.10)	-0.17 (0.86)		
Model 3 statistics			0.13	F(3, 4860) = 2.10 *p* = 0.10			0.06	F(3, 4858) = 0.96 *p* = 0.41			0.02	F(3, 2525) = 0.14 *p* = 0.94
Difference in Model 2 and Model 3			ΔR^2 = 0.00	F(1, 4860) = 0.17 *p* = 0.68			ΔR^2 = 0.00	F(1, 4858) = 0.02 *p* = 0.88			ΔR^2 = 0.00	F(1, 2525) = 0.03 *p* = 0.86

18 km	'there are lots of fun things to do where I live' (n = 2528)				'I wish I lived in a different house' (n = 2523)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.26 (-0.38, -0.15)	-4.44 (9.44 x10^6)			0.03 (-0.10, 0.16)	0.42 (0.67)		
Model 1 statistics			0.77	F(1, 2526) = 19.70 p = 9.44 x10^6			0.01	F(1, 2521) = 0.18 p = 0.67
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.11 (0.02, 0.20)	2.45 (0.01)			0.01 (-0.09, 0.11)	0.25 (0.81)		
Green space	-0.02 (-0.03, -0.01)	-4.17 (3.09 x10^5)			0.00 (-0.01, 0.01)	-0.36 (0.72)		
Model 2 statistics			1.66	F(2, 2525) = 21.36 p = 6.34 x10^{10}			0.01	F(2, 2520) = 0.11 p = 0.90
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	0.12 (0.02, 0.21)	2.43 (0.02)			-0.01 (-0.11, 0.10)	-0.14 (0.89)		
Green space	-0.02 (-0.03, -0.01)	-4.13 (3.73 x10^5)			0.00 (-0.01, 0.01)	-0.45 (0.65)		
Scenic level	-0.03 (-0.23, 0.16)	-0.35 (0.73)			0.13 (-0.09, 0.35)	1.16 (0.25)		
Model 3 statistics			1.67	F(3, 2524) = 14.27 p = 3.19 x10^9			0.06	F(3, 2519) = 0.52 p = 0.67
Difference in Model 2 and Model 3			ΔR^2 = 0.00	F(1, 2524) = 0.12 p = 0.73			ΔR^2 = 0.05	F(1, 2519) = 1.34 p = 0.25

18 km	'I wish there were different people in my neighbourhood' (n = 2525)				'I like where I live' (n = 2524)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.14 (-0.27, -0.02)	-2.25 (0.02)			0.04 (-0.06, 0.13)	0.76 (0.45)		
Model 1 statistics			0.20	F(1, 2523) = 5.05 p = 0.02			0.02	F(1, 2522) = 0.58 p = 0.45
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.04 (-0.06, 0.13)	0.73 (0.47)			0.01 (-0.06, 0.09)	0.35 (0.73)		
Green space	-0.01 (-0.02, 0.00)	-1.52 (0.13)			0.00 (-0.01, 0.01)	-0.29 (0.77)		
Model 2 statistics			0.31	F(2, 2522) = 3.95 p = 0.02			0.01	F(2, 2521) = 0.07 p = 0.93
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	0.04 (-0.06, 0.14)	0.83 (0.41)			0.00 (-0.08, 0.08)	0.01 (0.99)		
Green space	-0.01 (-0.02, 0.00)	-1.47 (0.14)			0.00 (-0.01, 0.01)	-0.37 (0.71)		
Scenic level	-0.05 (-0.26, 0.16)	-0.45 (0.65)			0.08 (-0.08, 0.25)	1.00 (0.32)		
Model 3 statistics			0.32	F(3, 2521) = 2.70 p = 0.04			0.05	F(3, 2520) = 0.38 p = 0.77
Difference in Model 2 and Model 3			ΔR^2 = 0.01	F(1, 2521) = 0.20 p = 0.65			ΔR^2 = 0.04	F(1, 2520) = 1.00 p = 0.32

19 km	Subjective Happiness (n = 4930)				Life Satisfaction (n = 4928)				Subjective Health (n = 2553)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only												
Scenic	0.00 (-0.05, 0.06)	0.13 (0.90)			-0.03 (-0.09, 0.02)	-1.10 (0.27)			-0.02 (-0.08, 0.05)	-0.58 (0.56)		
Model 1 statistics			0.00	$F(1, 4862) = 0.02$ $p = 0.90$			0.02	$F(1, 4860) = 1.21$ $p = 0.27$			0.01	$F(1, 2527) = 0.34$ $p = 0.56$
Model 2: Urban-rural classification + green space												
Urban-rural classification	-0.05 (-0.09, 0.00)	-2.13 (0.03)			-0.03 (-0.07, 0.01)	-1.36 (0.17)			0.00 (-0.05, 0.05)	0.00 (1.00)		
Green space	0.01 (0.00, 0.01)	2.34 (0.02)			0.00 (0.00, 0.01)	0.99 (0.32)			0.00 (-0.01, 0.01)	-0.18 (0.86)		
Model 2 statistics			0.11	$F(2, 4861) = 2.77$ $p = 0.06$			0.06	$F(2, 4859) = 1.40$ $p = 0.25$			0.01	$F(2, 2526) = 0.18$ $p = 0.83$
Model 3: Urban-rural classification + green space + scenic level												
Urban-rural classification	-0.04 (-0.09, 0.00)	-1.90 (0.06)			-0.03 (-0.08, 0.02)	-1.25 (0.21)			0.00 (-0.05, 0.05)	0.06 (0.95)		
Green space	0.01 (0.00, 0.01)	2.34 (0.02)			0.00 (0.00, 0.01)	0.99 (0.32)			0.00 (-0.01, 0.01)	-0.17 (0.87)		
Scenic level	-0.01 (-0.10, 0.08)	-0.24 (0.81)			0.00 (-0.10, 0.09)	-0.05 (0.96)			-0.01 (-0.12, 0.10)	-0.19 (0.85)		
Model 3 statistics			0.11	$F(3, 4860) = 1.86$ $p = 0.13$			0.06	$F(3, 4858) = 0.94$ $p = 0.42$			0.02	$F(3, 2525) = 0.13$ $p = 0.94$
Difference in Model 2 and Model 3			$\Delta R^2 = 0.00$	$F(1, 4860) = 0.06$ $p = 0.81$			$\Delta R^2 = 0.00$	$F(1, 4858) = 0.00$ $p = 0.96$			$\Delta R^2 = 0.00$	$F(1, 2525) = 0.04$ $p = 0.85$

19 km	'there are lots of fun things to do where I live' (n = 2528)				'I wish I lived in a different house' (n = 2523)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.26 (-0.38, -0.14)	-4.37 (1.29 x10^{5})			0.04 (-0.09, 0.17)	0.58 (0.56)		
Model 1 statistics			0.75	F(1, 2526) = 19.1 p = 1.29 x10^{5}			0.01	F(1, 2521) = 0.34 p = 0.56
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.11 (0.02, 0.20)	2.36 (0.02)			0.02 (-0.09, 0.12)	0.30 (0.77)		
Green space	-0.02 (-0.03, -0.01)	-4.09 (4.39 x10^{5})			0.00 (-0.01, 0.01)	-0.41 (0.68)		
Model 2 statistics			1.65	F(2, 2525) = 21.15 p = 7.74 x10^{10}			0.01	F(2, 2520) = 0.13 p = 0.88
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	0.11 (0.02, 0.21)	2.32 (0.02)			-0.01 (-0.12, 0.10)	-0.18 (0.86)		
Green space	-0.02 (-0.03, -0.01)	-4.06 (4.99 x10^{5})			0.00 (-0.01, 0.01)	-0.51 (0.61)		
Scenic level	-0.03 (-0.22, 0.17)	-0.27 (0.79)			0.16 (-0.06, 0.38)	1.42 (0.16)		
Model 3 statistics			1.65	F(3, 2524) = 14.12 p = 3.97 x10^{9}			0.09	F(3, 2519) = 0.76 p = 0.52
Difference in Model 2 and Model 3			ΔR^2 = 0.00	F(1, 2524) = 0.07 p = 0.79			ΔR^2 = 0.08	F(1, 2519) = 2.02 p = 0.16

19 km	'I wish there were different people in my neighbourhood' (n = 2525)				'I like where I live' (n = 2524)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.14 (-0.26, -0.01)	-2.16 (0.03)			0.04 (-0.06, 0.14)	0.79 (0.43)		
Model 1 statistics			0.18	F(1, 2523) = 4.66 p = 0.03			0.02	F(1, 2522) = 0.62 p = 0.43
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.04 (-0.06, 0.13)	0.74 (0.46)			0.02 (-0.06, 0.09)	0.45 (0.66)		
Green space	-0.01 (-0.02, 0.00)	-1.54 (0.12)			0.00 (-0.01, 0.01)	-0.40 (0.69)		
Model 2 statistics			0.32	F(2, 2522) = 4.09 p = 0.02			0.01	F(2, 2521) = 0.10 p = 0.90
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	0.04 (-0.06, 0.14)	0.78 (0.43)			0.00 (-0.08, 0.08)	0.07 (0.94)		
Green space	-0.01 (-0.02, 0.00)	-1.52 (0.13)			0.00 (-0.01, 0.01)	-0.48 (0.63)		
Scenic level	-0.03 (-0.24, 0.18)	-0.27 (0.79)			0.09 (-0.07, 0.26)	1.08 (0.28)		
Model 3 statistics			0.33	F(3, 2521) = 2.75 p = 0.04			0.05	F(3, 2520) = 0.46 p = 0.71
Difference in Model 2 and Model 3			ΔR^2 = 0.00	F(1, 2521) = 0.07 p = 0.79			ΔR^2 = 0.05	F(1, 2520) = 1.16 p = 0.28

20 km	Subjective Happiness (n = 4930)				Life Satisfaction (n = 4928)				Subjective Health (n = 2553)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only												
Scenic	0.00 (-0.05, 0.06)	0.13 (0.89)			-0.03 (-0.09, 0.03)	-1.04 (0.30)			-0.02 (-0.09, 0.04)	-0.66 (0.51)		
Model 1 statistics			0.00	$F(1, 4862) = 0.02$ $p = 0.89$			0.02	$F(1, 4860) = 1.09$ $p = 0.30$			0.02	$F(1, 2527) = 0.44$ $p = 0.51$
Model 2: Urban-rural classification + green space												
Urban-rural classification	-0.04 (-0.09, 0.00)	-1.94 (0.05)			-0.03 (-0.07, 0.02)	-1.26 (0.21)			0.00 (-0.06, 0.05)	-0.15 (0.88)		
Green space	0.01 (0.00, 0.01)	2.15 (0.03)			0.00 (0.00, 0.01)	0.90 (0.37)			0.00 (-0.01, 0.01)	-0.04 (0.96)		
Model 2 statistics			0.10	$F(2, 4861) = 2.37$ $p = 0.09$			0.05	$F(2, 4859) = 1.28$ $p = 0.28$			0.02	$F(2, 2526) = 0.19$ $p = 0.82$
Model 3: Urban-rural classification + green space + scenic level												
Urban-rural classification	-0.04 (-0.09, 0.01)	-1.70 (0.09)			-0.03 (-0.08, 0.02)	-1.18 (0.24)			0.00 (-0.06, 0.05)	-0.05 (0.96)		
Green space	0.01 (0.00, 0.01)	2.16 (0.03)			0.00 (0.00, 0.01)	0.90 (0.37)			0.00 (-0.01, 0.01)	-0.03 (0.98)		
Scenic level	-0.01 (-0.11, 0.08)	-0.29 (0.77)			0.00 (-0.10, 0.10)	0.01 (0.99)			-0.01 (-0.12, 0.09)	-0.27 (0.79)		
Model 3 statistics			$\Delta R^2 = 0.10$	$F(3, 4860) = 1.61$ $p = 0.19$			0.05	$F(3, 4858) = 0.85$ $p = 0.46$			$\Delta R^2 = 0.02$	$F(3, 2525) = 0.15$ $p = 0.93$
Difference in Model 2 and Model 3			$\Delta R^2 = 0.00$	$F(1, 4860) = 0.09$ $p = 0.77$			$\Delta R^2 = 0.00$	$F(1, 4858) = 0.00$ $p = 0.99$			$\Delta R^2 = 0.00$	$F(1, 2525) = 0.07$ $p = 0.79$

20 km	'there are lots of fun things to do where I live' (n = 2528)				'I wish I lived in a different house' (n = 2523)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.26 (-0.38, -0.14)	-4.33 (1.52 x10^{5})			0.05 (-0.09, 0.18)	0.71 (0.48)		
Model 1 statistics			0.74	F(1, 2526) = 18.79 p = 1.52 x10^{5}			0.02	F(1, 2521) = 0.50 p = 0.48
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.11 (0.02, 0.00)	2.29 (0.02)			0.01 (-0.09, 0.12)	0.28 (0.78)		
Green space	-0.02 (-0.03, -0.01)	-4.02 (6.03 x10^{5})			0.00 (-0.01, 0.01)	-0.37 (0.71)		
Model 2 statistics			1.62	F(2, 2525) = 20.84 p = 1.05 x10^{9}			0.01	F(2, 2520) = 0.10 p = 0.91
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	0.11 (0.01, 0.21)	2.25 (0.02)			-0.01 (-0.12, 0.10)	-0.23 (0.82)		
Green space	-0.02 (-0.03, -0.01)	-3.99 (6.72 x10^{5})			0.00 (-0.01, 0.01)	-0.47 (0.64)		
Scenic level	-0.03 (-0.22, 0.17)	-0.27 (0.79)			0.17 (-0.05, 0.39)	1.52 (0.13)		
Model 3 statistics			1.63	F(3, 2524) = 13.91 p = 5.36 x10^{9}			0.10	F(3, 2519) = 0.84 p = 0.47
Difference in Model 2 and Model 3			ΔR^2 = 0.00	F(1, 2524) = 0.07 p = 0.79			ΔR^2 = 0.09	F(1, 2519) = 2.32 p = 0.13

20 km	'I wish there were different people in my neighbourhood' (n = 2525)				'I like where I live' (n = 2524)			
	β (95% CIs)	t-value (p)	R^2	F statistic	β (95% CIs)	t-value (p)	R^2	F statistic
Model 1: Scenic only								
Scenic	-0.14 (-0.27, -0.01)	-2.12 (0.03)			0.04 (-0.06, 0.14)	0.76 (0.45)		
Model 1 statistics			0.18	F(1, 2523) = 4.51 p = 0.03			0.02	F(1, 2522) = 0.58 p = 0.45
Model 2: Urban-rural classification + green space								
Urban-rural classification	0.03 (-0.07, 0.13)	0.68 (0.50)			0.02 (-0.06, 0.09)	0.39 (0.70)		
Green space	-0.01 (-0.02, 0.00)	-1.48 (0.14)			0.00 (-0.01, 0.01)	-0.34 (0.73)		
Model 2 statistics			0.31	F(2, 2522) = 3.98 p = 0.02			0.01	F(2, 2521) = 0.08 p = 0.92
Model 3: Urban-rural classification + green space + scenic level								
Urban-rural classification	0.04 (-0.07, 0.15)	0.72 (0.47)			0.00 (-0.08, 0.08)	0.04 (0.97)		
Green space	-0.01 (-0.02, 0.00)	-1.46 (0.14)			0.00 (-0.01, 0.01)	-0.40 (0.69)		
Scenic level	-0.03 (-0.24, 0.19)	-0.24 (0.81)			0.09 (-0.08, 0.25)	1.00 (0.32)		
Model 3 statistics			0.32	F(3, 2521) = 2.67 p = 0.05			0.05	F(3, 2520) = 0.39 p = 0.76
Difference in Model 2 and Model 3			ΔR^2 = 0.00	F(1, 2521) = 0.06 p = 0.81			ΔR^2 = 0.04	F(1, 2520) = 1.01 p = 0.32